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Optimizing Facial Expression Recognition with Biogeography-Based Feature Selection

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Abstract

Facial expression recognition remains a challenging task in computer vision due to factors such as occlusion, variable lighting, and camera angles. Efficient extraction and selection of relevant features are crucial for accurate recognition. This paper introduces a novel metaheuristic-based approach for feature selection and classification using a Biogeography-Based Optimization (BBO) algorithm. The BBO algorithm optimizes the recognition accuracy of a Support Vector Machine (SVM) by selecting the most relevant features through cross-validation accuracy as the evaluation criterion. The proposed BBO-SVM model is tested on three public databases—JAFFE, MUG, and CK+—and demonstrates superior performance compared to traditional filter-based approaches. Notably, the model achieves a recognition accuracy of [insert specific accuracy], outperforming several existing methods. This study highlights the potential of BBO for enhancing facial expression recognition systems.

Keywords: Facial Expression Recognition System;, Biogeography-Based Optimization; Feature Selection; Support Vector Machine; Wrapper-Based Feature Selection

1 Introduction

The development of intelligent systems facilitating human-computer interaction has sparked significant interest in computer vision applications across various domains, including healthcare, agriculture, intrusion detection, and surveillance. Among these, automatic facial expression recognition systems have been a prominent area of research for several decades. The process of detecting expressions from digital facial images is typically divided into four stages: face detection, feature extraction, feature selection, and expression classification. Face detection is the initial and most crucial step, as the face conveys essential information about a person's emotions through various gestures, such as eye and lip movements. This step isolates the facial region from the image background, enabling subsequent processes to focus on relevant data. Following face detection, the feature extraction process retrieves pertinent information from the face, which is essential for accurate expression recognition. This paper primarily focuses on the feature selection process[1], examining the impact of various feature selection mechanisms available in the literature to extract an optimal subset of features, thereby enhancing overall system performance. Feature selection is a critical step, as robust expression classification relies on the identification of efficient and distinct features. By reducing redundant and irrelevant information, the feature selection process aims to represent input features more effectively, improving classifier recognition rates and reducing the dimensionality of the feature set. Feature selection methods are broadly categorized into three types: filter methods, wrapper methods, and embedded methods. Filter methods rank features based on intrinsic dataset properties without considering the classifier model, making them popular for high-dimensional datasets due to their scalability and low risk of overfitting.

Wrapper methods, on the other hand, use optimization techniques to select feature subsets based on classifier evaluation, taking into account feature dependencies. Embedded methods combine aspects of both filter and wrapper methods, utilizing

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a built-in approach for feature selection. In this study, we evaluate the performance of an expression recognition system after applying two filter-based feature selection methods. Additionally, we propose a novel Biogeography-Based Optimization and Support Vector Machine (BBO-SVM) approach for automatic facial expression recognition. Experiments are conducted on three publicly available facial expression databases—JAFFE, MUG, and CK+—with the proposed system achieving promising classification accuracies across all three datasets. The proposed work extends our previous research [2], which introduced a framework for the automatic recognition of facial expressions based on a fusion of deep and geometric features. In this study, we aim to maximize recognition accuracy by selecting the best-performing features from the original feature set using an evolutionary biogeography-based optimization algorithm. The key contributions of this paper are as follows:

- **Feature Extraction Process:** This paper employs a fusion of geometric and deep features for feature extraction. Geometric features include the x and y coordinates of 49 landmark points on the face, constructing a feature vector of 98 values. Deep features are extracted from images using a deep convolutional neural network, with 84 features obtained just before the softmax classification layer. These geometric and deep features are then concatenated to form a final feature vector containing 113 features.

- **BBO-Based Feature Selection and Optimization:** The generated feature set is optimized using the metaheuristic Biogeography-Based Optimization algorithm, which selects the best-performing features with the goal of maximizing classification accuracy.

- **Emotion Classification Using SVM:** Emotion classification is performed using an SVM model, which is integrated into the BBO algorithm as a fitness function. The BBO algorithm maximizes the classifier's cross-validation accuracy while selecting the optimal feature subset.

The classification results of the proposed BBO-SVM method are compared with two filter-based feature selection methods, namely mutual information and ANOVA. The results indicate that the proposed BBO-SVM approach outperforms these filter-based methods and achieves commendable recognition rates compared to other works in the literature. The remainder of the paper is organized as follows: Section 2 presents a literature survey of existing feature selection mechanisms, Section 3 details the databases used for system validation, Section 4 discusses the proposed methodology in detail, and Section 5 concludes the paper and outlines future research directions.

2 Related Works

Various feature selection methods have been studied and proposed in the literature. A study proposed in [3] utilized an iterative feature selection method based on Random Forest to reduce the appearance-based features extracted from face images. The results demonstrated a 22% improvement in performance with the use of this feature selection process. Another approach involved a hybrid of wrapper and filter feature selection mechanisms based on ant colony optimization, which outperformed many state-of-the-art methods and showed promising results [4]. Additionally, a wrapper-based method employing a genetic algorithm was introduced to reduce log-Gabor features, aiming to minimize classification error and achieve better results compared to filter-based methods [5]. Lajevardi and Hussain [6] presented an automatic facial expression recognition system that utilized a combination of filter and wrapper-based techniques to select the most informative features. The framework was validated through experiments on the CK+ and JAFFE databases, yielding desirable results. Similarly, a feature selection mechanism based on mutual information was employed to reduce primitive and complex features extracted from face images [7], with validation performed on the JAFFE dataset. Another study conducted feature selection on scale-invariant feature transform-based features using the Grey Wolf optimization metaheuristic algorithm, which were then used for emotion classification [8]. In the realm of social cognition, Zwick [9] examined the impact of reduced facial mimicry on expression recognition and depressive measures. An intelligent facial expression system was also proposed, which extracts facial features using modified local binary pattern descriptors and optimizes them with a variant of the Firefly algorithm [10]. Further research utilized spatial-temporal features, enhancing dynamic face information through a weight-based strategy for automatic facial expression recognition. Experiments on the CK+ and MMI face datasets demonstrated good recognition accuracies [11]. Moreover, a rough set theory-based self-learning feature reduction framework was introduced, achieving a high emotion classification rate by focusing on the most effective features in the mouth region [12]. In another study, a binary particle swarm optimization technique with an enhanced mutation operator was proposed to mitigate the premature convergence problem during feature selection. This wrapper approach employed a support vector machine for expression classification [13]. Lastly, Zhang et al. [14] presented a system that generates low-dimensional features by applying local fisher discriminant analysis (LFDA) on extracted local binary pattern (LBP) features, followed by classification using an SVM model built on the reduced feature set. The review suggests that feature selection is a critical step in developing an automatic facial expression recognition system, as it aids in selecting the most effective feature subset, thereby leading to higher classification accuracy and overall system performance. The remaining sections of this paper present a novel BBO-SVM feature selection approach, which identifies the optimal feature subset from deep and geometric features extracted from face images and performs classification using the SVM model. The proposed framework is evaluated on the datasets discussed in the next section.

3 Methods

3.1 Datasets Used

Three publicly available facial image databases were used in this study. These datasets are described in detail below:

3.1.1 JAFFE

The Japanese Female Facial Expression (JAFFE) database [15] contains 213 sample images from 10 female models of Japanese origin. The images are posed in seven universal facial expressions: angry, disgust, happiness, fear, sad, surprise, and neutral. All 213 images, which are in grayscale format, were used in this study for performing experiments. Figure 1 depicts sample images from the JAFFE dataset across six universal emotion classes.

Figure 1: Sample images from the JAFFE dataset

3.1.2 MUG

The Multimedia Understanding Group (MUG) database [16] contains images of 86 subjects posing in seven different facial expressions. Out of these, images of 52 subjects (including 52 men and 35 women) are publicly available. The subjects, aged between 20 to 35 years, are of Caucasian origin. This study used 712 randomly selected images from this dataset, covering the seven universal emotion classes. Figure 2 shows some sample images from the MUG dataset.

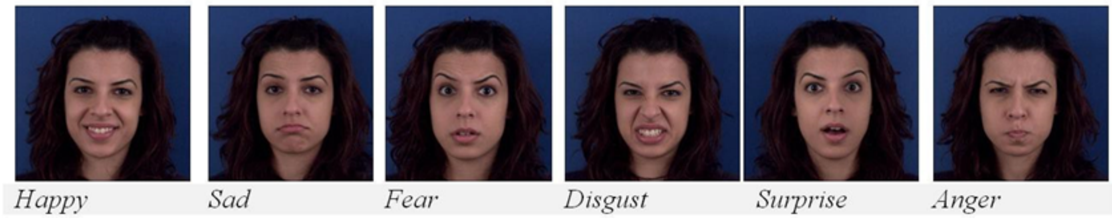

Figure 2: Sample images from the MUG dataset

3.1.3 CK+

The extended Cohn-Kanade (CK+) database [17], released in 2010, contains 593 video sequences collected from 123 subjects aged between 18 to 50 years, from various origins and genders. For this study, 325 images of 118 subjects were selected from the video sequences in the dataset to perform the experiments. Sample images from the CK+ dataset are depicted in Figure 3.

Figure 3: Sample images from the CK+ dataset

The number of samples and subjects from each dataset used in this study are summarized in Table 1.

The proposed BBO-SVM feature selection and classification framework for facial expression recognition operates on the deep and geometric features [2] extracted from the input face images. The complete process of automatic facial expression recognition can be divided into four stages, as depicted in Figure 4.

Table 1: Details of the datasets used

Dataset	No. of Samples	No. of Subjects
JAFFE	213	10
MUG	712	52
CK+	325	118

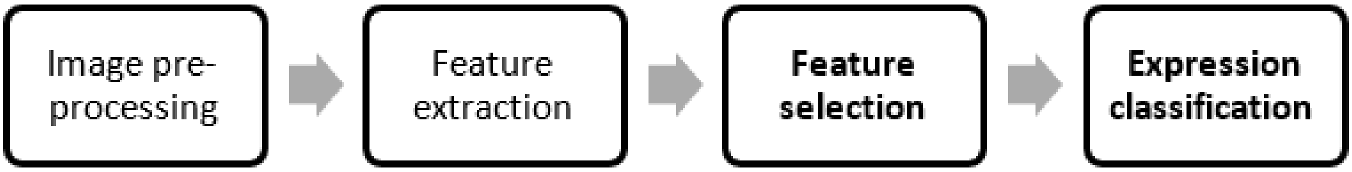

Figure 4: Different phases of the facial expression recognition system

3.2 Pre-processing and Feature Extraction

The pre-processing of the input images is the first step in building an automatic facial expression recognition system. This step is crucial for concealing unwanted details or enhancing essential details in the image. In this study, face detection is performed on the input image using the Viola-Jones algorithm [18] as part of the pre-processing step, since the face contains all the important information required for detecting expressions. After the face is extracted, a low-pass Gaussian filter is applied to remove noise from the image. Additionally, the illumination conditions of the image are enhanced using the contrast histogram equalization technique to capture sharp details such as edges and face contours. The pre-processed image is then used for extracting relevant features. Two kinds of features are used in this work: 1) Geometric features, and 2) Deep features.

3.2.1 Geometric Features

The geometric features are extracted from the face region in the form of x and y coordinates of various facial points. A total of 49 landmark points are selected on the face region using the iPar-CLR method [19], forming a feature vector with 98 coordinate values, as shown in Figure 5. In addition to these features, 15 distinct distance values between the facial points are calculated using the Euclidean distance and concatenated with the 98-dimensional feature vector, resulting in a final feature vector of size 113.

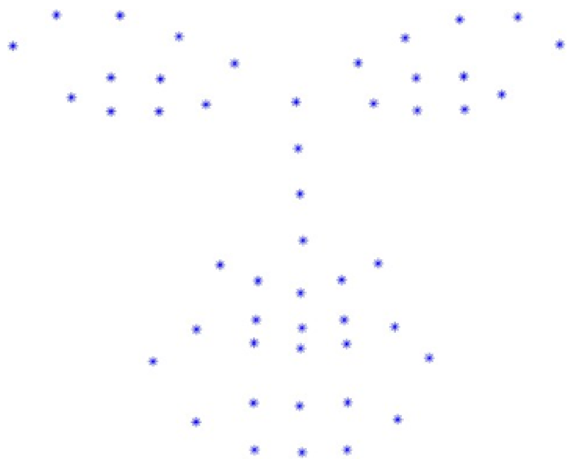

Figure 5: Facial landmark points used for feature vector construction.

3.2.2 Deep Features

Deep features are highly effective in detecting facial expressions due to the rich information they capture and the intricate details they provide. In this study, deep features are extracted from a 6-layer convolutional neural network (CNN) built from scratch [2]. The architecture of the network used for deep feature extraction is shown in Figure 6. These features are extracted from the network after the fully connected layers and just before the final classification layer, resulting in a feature vector with 84 deep features. These geometric and deep features are combined to form the final feature vector. To select the best-performing features and maximize the recognition rate of the system, feature selection is performed after the feature extraction process.

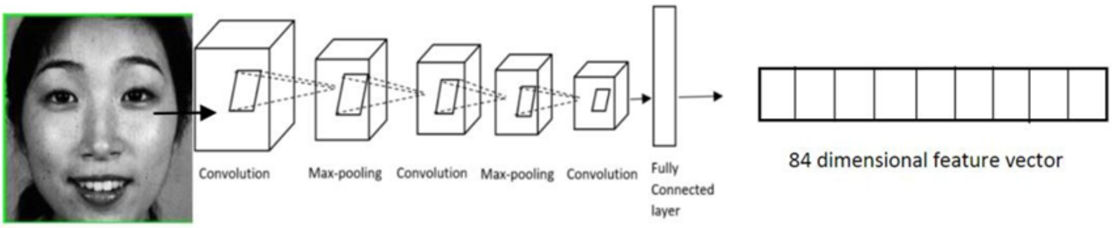

Figure 6: Deep features extraction process.

3.3 Feature Selection

Feature selection, or attribute selection, is the process of identifying the most contributing features while eliminating the least contributing ones. The goal is to reduce the dimensionality of the feature set while maximizing the performance of the classifier trained on these features. This paper proposes a wrapper-based feature selection approach that employs a Biogeography-Based Optimization (BBO) technique for optimal feature subset selection. The selection is based on the cross-validation accuracy of the Support Vector Machine (SVM), used as the fitness function to evaluate the performance of the subset on the classifier. The proposed approach iteratively performs feature optimization to maximize the expression recognition accuracy of the SVM. In addition, some filter-based methods were used to select the most appropriate features from the original feature vector. The performance of these filter-based methods is compared with the proposed wrapper-based BBO-SVM method. This section discusses the different feature selection mechanisms used in this paper.

3.3.1 Mutual Information

Mutual information feature selection [20] is based on information gain theory. Information gain is calculated by determining the amount of information gained by selecting or not selecting a particular feature in the feature set. Mutual information between two variables A and B can be defined by the Eq. 1:

$$I(A,B) = \int\int p(a,b)\log\left(\frac{p(a,b)}{p(a)p(b)}\right) dadb \tag{1}$$

where $p(a,b)$ represents the joint probability function of A and B, and $p(a)$ and $p(b)$ are the marginal distribution functions. Mutual information is a measure of similarity between $p(a,b)$ and the product of the marginal distributions $p(a)$ and $p(b)$. If the variables are completely independent, the mutual information will be zero, indicating that $p(a,b) = p(a)p(b)$. The feature selection mechanism aims to maximize this mutual information between the target variable b and the selected set of features.

3.3.2 ANOVA F-test Feature Selection

The Analysis of Variance (ANOVA) feature selection method [21] is a statistical measure in which feature selection is performed by analyzing the responses of the feature variables based on certain conditions. Two key measures are used in this method: p-score and F-score. The F-score determines the ratio between the mean variance values of two samples.

The p-score is the probability of discarding the F-score. Features are ranked based on their importance, and those that do not show significant differences in the target classes are discarded. A predefined number of higher-ranked features are selected to be part of the final feature set for emotion classification.

3.3.3 Biogeography-Based Optimization (BBO)

The BBO algorithm belongs to the class of metaheuristic algorithms and was first introduced by Dan Simon [22] in 2008. It is based on the natural process of biogeography, i.e., the study of the distribution of biological species. Species or populations are usually distributed within a geographical area with defined boundaries known as habitats. Each habitat has a Habitat Suitability Index (HSI), representing the desirability of a habitat for accommodating life. Factors such as temperature, rainfall, and vegetation patterns contribute to this HSI and are termed as Suitability Index Variables (SIVs). Populations tend to be higher in high-HSI habitats due to better conditions. However, due to high population density and competition, some native species migrate to neighboring habitats. This migration is termed emigration, and thus, emigration rates are high for high-HSI habitats. Conversely, the migration of species into high-HSI habitats is low due to the already abundant population, resulting in low immigration rates. In low-HSI habitats, immigration rates are higher compared to emigration rates. The reason for the high immigration rate is not the appropriateness of the habitat but its ability to accommodate more species. As varied species occupy the low-HSI habitats, the HSI tends to improve. However, if the HSI does not improve due to a lack of resources, some species may become extinct, creating opportunities for new species to move into the habitat. In the feature selection problem, each feature in the original feature vector is assigned a value considered as the SIV, constructing a real number array. Each candidate solution of the population can be thought of as a habitat, and the goodness of the candidate solution, or fitness function, is analogous to the HSI. The HSI of any habitat h can be represented as a function of SIVs, as given by the Eq. 2:

$$HSI(h) = f(SIV_i) \tag{2}$$

A candidate solution is a subset of selected features or SIVs. This indicates that a solution with a good HSI value shares the features or SIVs with the weaker solutions [23]. This migration is influenced by emigration and immigration rates, denoted by μ and λ, respectively. Figure 7 depicts the simple linear migration model, where E is the maximum emigration rate and I is the maximum immigration rate. The values of both E and I are set to 1.

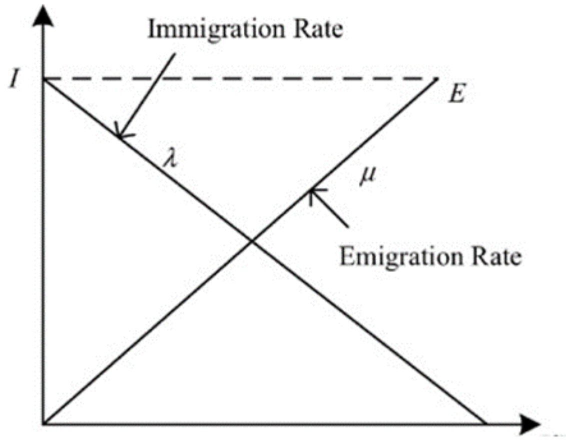

Figure 7: BBO migration model

In the proposed work, the best-performing features from the original feature set obtained during the feature extraction step are determined using the BBO algorithm. The SVM learning model is deployed, and its cross-validation accuracy is used to evaluate the performance of the selected feature subset, as shown in Figure 8.

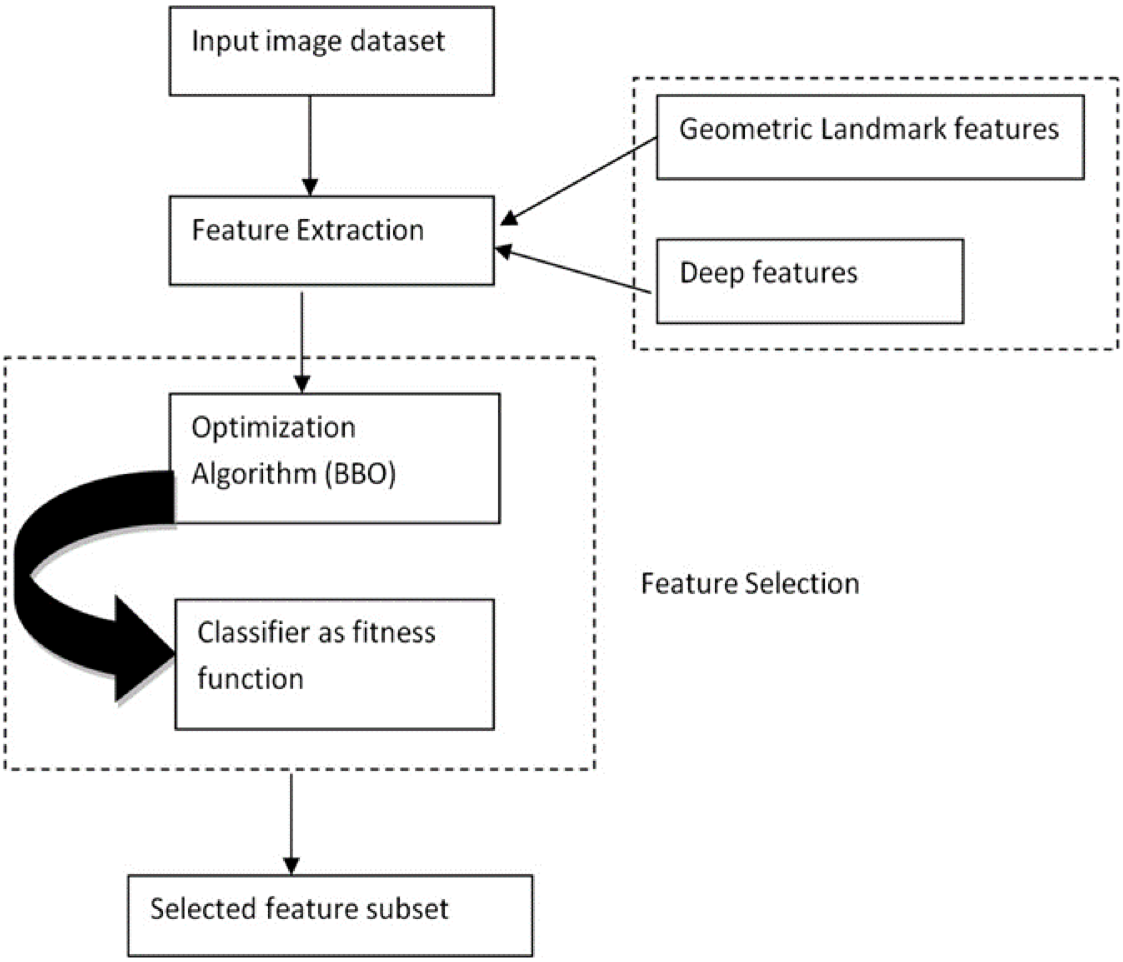

Figure 8: The proposed facial expression recognition system

3.4 Feature Selection Mechanism

The complete process of the feature selection mechanism proposed in this study is depicted in Figure 9. The detailed BBO-SVM algorithm for performing feature selection is presented in Algorithm 1 below.

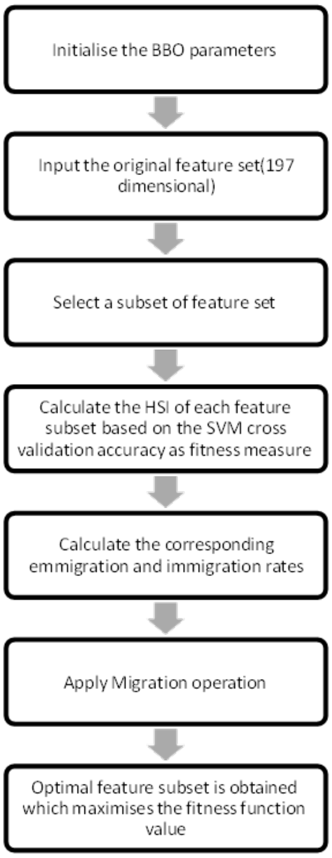

Figure 9: Proposed feature selection mechanism.

Migration operation [24] is performed so that the good habitats can share SIVs with the poor habitats. Emigrating habitats tend to share features with immigrating habitats. The value of the immigration rate is used as a basis to decide whether the habitat should be altered or not. The individual emigration and immigration rates for n habitats in the ith iteration can be calculated using the Eqns. 3 and 4:

$$\mu_i = \frac{Ei}{n} \tag{3}$$

$$\Lambda_i = I\left(1 - \frac{i}{n}\right) \tag{4}$$

A mutation operation is performed in the BBO algorithm to randomly alter the habitats using the mutation probability, which is a pre-determined value. The mutation rate for a solution s is given by the Eq 5:

$$\text{Mutation rate} = \text{Maximum mutation rate} \times \left(1 - \frac{P_s}{P_m}\right) \tag{5}$$

where P_s is the probability of the sth individual, and P_m is the maximum mutation probability.

The BBO optimization algorithm used in this work provides the optimal set of features based on the combination that maximizes the SVM cross-validation accuracy, making the emotion recognition process highly efficient and robust. The technique ensures that none of the features in the selected feature subset are redundant within a habitat, and the same number of features is selected for each candidate solution.

3.5 Expression Classification

The task of performing expression classification is an integral part of the feature selection mechanism discussed in the previous section. Since the wrapper-based approach is used for feature selection, the Support Vector Machine (SVM) classification model is embedded inside the BBO algorithm as the fitness function. SVM [25] is widely used for classification tasks and has consistently delivered strong classification results. Originally introduced by Vapnik [26] in statistical learning theory, SVM works by constructing a hyperplane that maximizes the distance between output classes.

4 Results and Discussion

The proposed system was evaluated on three publicly available datasets: JAFFE, MUG, and CK+. Facial expression classification was performed using the SVM classification model on each feature subset combination selected by the optimization

Algorithm 1 BBO-SVM Feature Selection Algorithm

Initialize the BBO parameters.
Generate a random population of initial habitats.
Calculate the fitness value or HSI for each habitat in the population. This fitness value corresponds to the cross-validation accuracy obtained by the SVM classification model for the selected feature subset combination.
for Generation = 1 to G **do**
  Calculate emigration rate μ and immigration rate Λ.
  Perform the migration operation to modify each elite habitat and recompute the HSI value.
  Perform the mutation operation to modify each non-elite habitat and recompute the HSI value.
  if maximum number of generations reached or optimal solution found **then**
    Terminate the loop.
  end if
end for
Output the selected feature subset and the maximum fitness value obtained.

algorithm, and the best feature subset—i.e., the combination yielding the maximum classification accuracy—was chosen. The initial feature vector, containing geometric and deep features, was passed through the BBO-SVM framework. The population size was set to 30, and the algorithm was run for 50 generations to obtain maximum recognition accuracy. The mutation probability was set to 0.05, and the emigration and immigration rates were set to 1, as shown in Table 2.

Table 2: Values of parameters used for the BBO algorithm

Parameter	Value
No. of generations (G)	50
Population size (N)	30
Max Emigration rate (E)	1
Max Immigration rate (I)	1
No. of elites retained	2
Mutation Probability (P_m)	0.05

Originally, SVM supports only binary or two-class classification. However, this work requires performing multiclass classification to classify the input into one of the seven emotion classes based on facial expressions. The one-versus-one strategy was used, constructing a multi-class classification model by building separate classifiers for each different pair of output labels. This leads to $\frac{N(N-1)}{2}$ classifiers being built, where N is the number of output classes. The LibSVM library was deployed for evaluating the candidate solutions obtained in each generation of the BBO algorithm. The radial basis function (RBF) was used as a kernel in the SVM, and 10-fold cross-validation was performed to ensure the reliability of classification results.

To compare the performance of the proposed wrapper-based feature selection mechanism, two other filter-based feature selection approaches—Mutual Information and ANOVA feature selection—were also applied to all three databases. It was observed that the proposed BBO-SVM feature selection mechanism outperformed the filter-based approaches. The effect of applying a feature selection mechanism on the extracted features is evident from the results, as the recognition accuracy of the facial expression recognition system increased compared to the earlier system [2] that performed the classification task immediately after the feature extraction process.

Table 3: Recognition accuracy achieved on JAFFE dataset

Method Used	Recognition Accuracy
SVM classification without any feature selection method	81.39%
Mutual Information Feature Selection	83.7%
ANOVA Feature Selection	86.04%
Proposed BBO-SVM Feature Selection	95.34%

Table 3 presents the recognition accuracy values obtained for the experiments performed on the JAFFE dataset. The recognition accuracy of 81.39% [2] was achieved when no feature selection mechanism was applied to the extracted combination of deep and geometric features. The accuracy improved to 83.7% and 86.04% when Mutual Information and ANOVA feature selection methods were applied to the extracted features, as shown in Figure 10. The results demonstrate that the proposed wrapper-based BBO-SVM feature selection model outperformed the filter-based approaches. The recognition performance of the facial expression recognition system improved by 13.95% compared to the framework that did not use any feature selection mechanism.

The highest recognition accuracy of 96.92% was achieved on the MUG database using the proposed wrapper-based approach, compared to the filter-based approaches which achieved recognition accuracy values of 87.4% and 89.69%, as

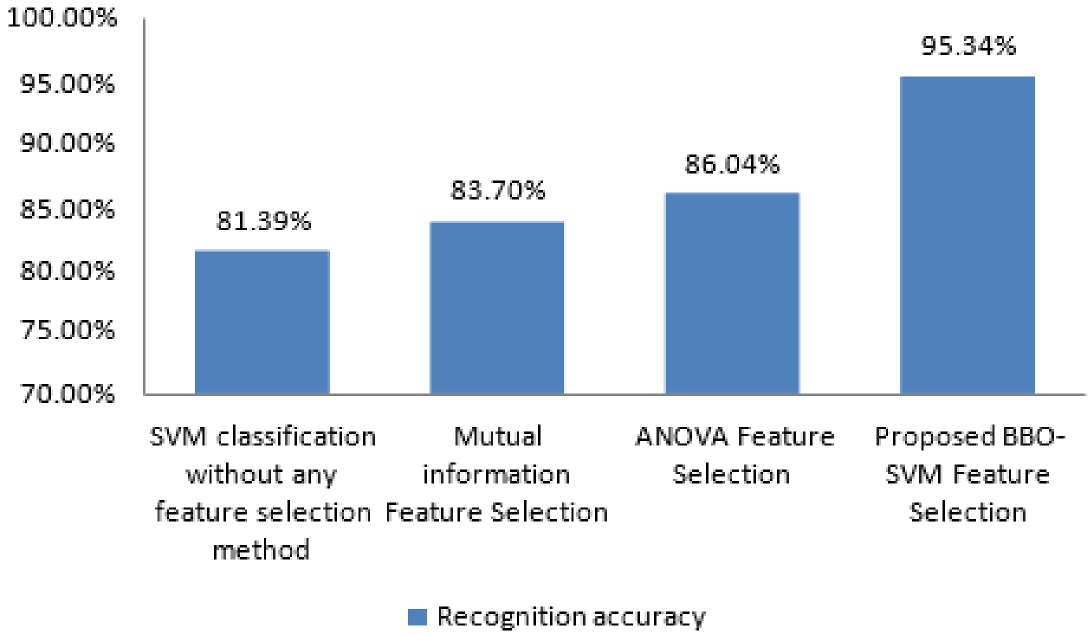

Figure 10: Comparison of recognition accuracy achieved using different methods on JAFFE dataset.

shown in Table 4. Figure 11 depicts the bar graph plot comparing the accuracies obtained after applying the feature selection mechanisms on the original feature vector.

Table 4: Recognition accuracy achieved on MUG dataset

Method Used	**Recognition Accuracy**
SVM classification without any feature selection method	86.01%
Mutual Information Feature Selection	87.4%
ANOVA Feature Selection	89.69%
Proposed BBO-SVM Feature Selection	96.92%

The results obtained on the CK+ dataset also validate the proposed work, as a high recognition accuracy of 98.5% was achieved using the proposed BBO-SVM approach, as shown in Table 5. The Mutual Information and ANOVA feature selection approaches also showed promising recognition accuracies of 86.1% and 88.3%, respectively, as depicted in Figure 12.

Table 5: Recognition accuracy achieved on CK+ dataset

Method Used	**Recognition Accuracy**
SVM classification without any feature selection method	84.5%
Mutual Information Feature Selection	86.1%
ANOVA Feature Selection	88.3%
Proposed BBO-SVM Feature Selection	98.5%

The experiments performed on all three databases suggest that the recognition accuracy of the facial expression recognition system can be improved by using feature selection mechanisms, as shown in Figure 13. The proposed BBO-SVM approach has proven to achieve good recognition accuracy on all the databases used in this study. As mentioned earlier, the algorithm was run for 50 generations, as it was observed that the recognition accuracy remained constant during the last few generations and did not improve further.

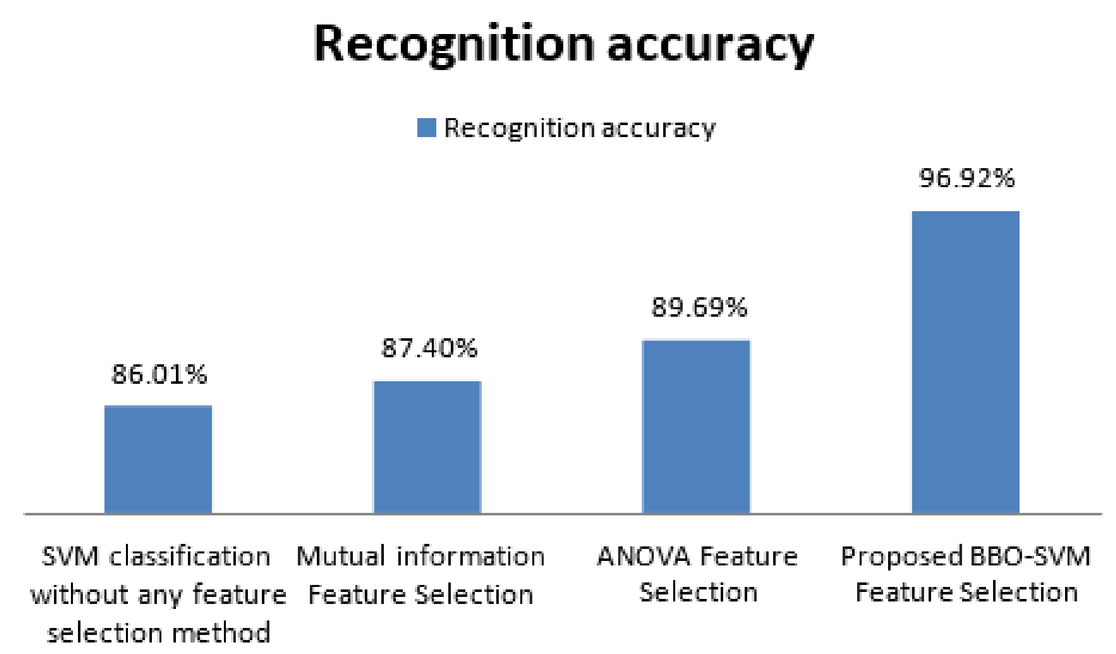

Figure 11: Comparison of recognition accuracies using different methods on the MUG dataset.

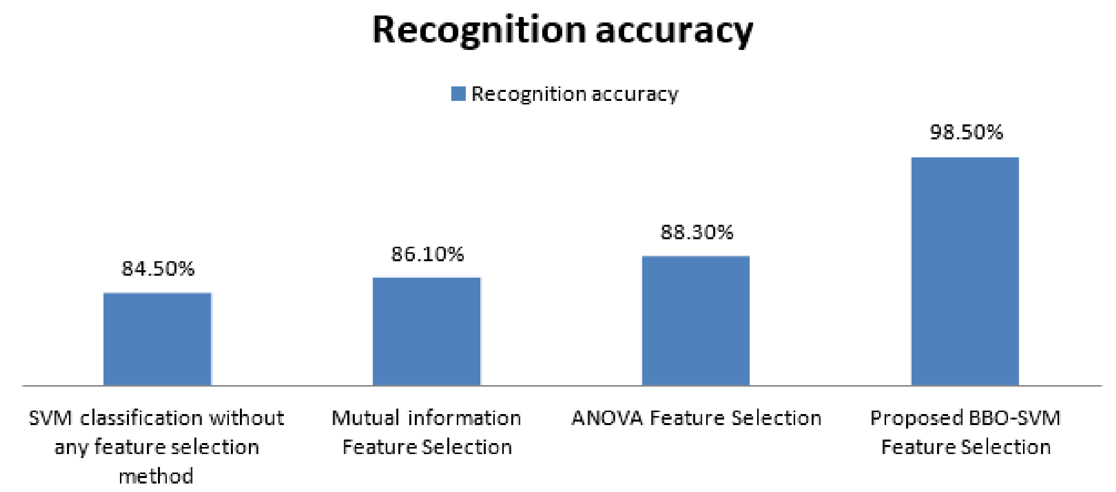

Figure 12: Comparison of recognition accuracies achieved using different methods on CK+ dataset.

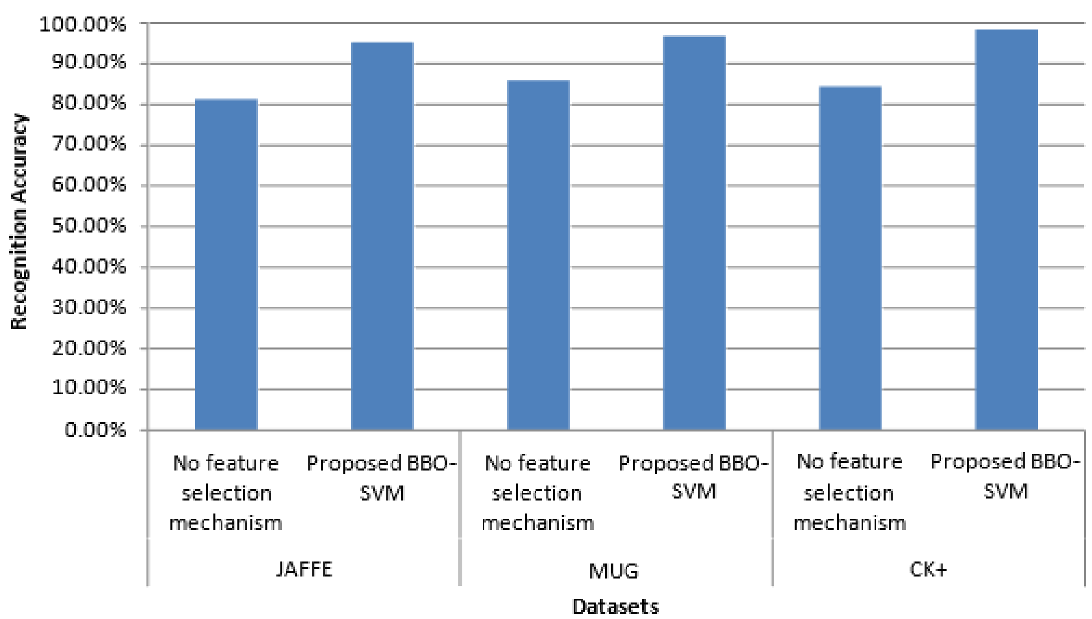

Figure 13: Effect of using feature selection mechanism on recognition accuracy of the facial expression recognition system.

The proposed system is also compared with other similar works available in the literature, as shown in Table 6. The results indicate that the proposed work has achieved comparable and even better results than some of the similar systems that perform the expression classification task.

Table 6: Comparison of the proposed facial expression recognition system with other works available in the literature

Study	JAFFE	CK+	MUG
[27]	89.6%	88.9%	–
[28]	–	94.93% (Highest accuracy)	–
[29]	92.31%	–	–
[30]	92.39%	–	92.60%
[31]	94.37%	–	95.24%
[32]	–	98.0%	97.2%
[33]	–	97.8%	95.5%
Proposed BBO-SVM	95.34%	98.5%	96.92%

5 Conclusion

In this paper, an optimization-based feature selection approach is presented for building a robust expression classification system that classifies input images into one of the seven universal emotion classes: angry, disgust, fear, happy, sad, surprise, and neutral. The meta-heuristic Biogeography-Based Optimization (BBO) algorithm is utilized to obtain an optimized subset of the feature vector, and the Support Vector Machine (SVM) is deployed as the classifier, integrated within the BBO algorithm. The cross-validation accuracy obtained for each combination of features in the selected subset is used as the cost or fitness value in the algorithm, which is maximized by performing migration and mutation operations within the BBO framework. The proposed BBO-SVM method works by improving the quality of habitats by selecting the most appropriate features and discarding the weaker ones. Additionally, the number of features selected in each generation is not fixed, allowing for dynamic generation of feature subset dimensions after each generation to ensure all relevant features are selected. The method was evaluated using three publicly available datasets: JAFFE, MUG, and CK+. The results demonstrate that the proposed method not only outperformed filter-based approaches such as Mutual Information and ANOVA feature selection but also surpassed various similar systems available in the literature. The highest recognition rate was achieved on the CK+ database with an accuracy of 98.5%, followed by 96.97% on the MUG dataset and 95.34% on the JAFFE dataset. In the future, other meta-heuristic algorithms such as Ant Colony Optimization, Particle Swarm Optimization, and Grey Wolf Optimization could be explored for feature selection. Additionally, hybrid methods combining two or more meta-heuristic techniques could be proposed. Furthermore, different classification models such as Random Forest and Naive Bayesian Classifier could be used in the wrapper approach to potentially enhance the performance of the system.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Author Contribution

Garima Sharma: Conceptualization, Methodology, Investigation, Visualization, Writing - original draft, review, and editing. **Latika Singh**: Resources, Validation, Writing - original draft, review, and editing.

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Deep Learning-Based Diagnosis of Pneumonia Using Convolutional Neural Networks

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Abstract

Pneumonia is a respiratory illness characterized by lung inflammation, often caused by pathogens such as viruses, bacteria, or fungi. Timely detection of pneumonia is crucial for effective treatment. While chest X-rays are commonly used for diagnosis, manual interpretation can be time-consuming, particularly in areas with limited access to trained radiologists. Currently, deep learning models have emerged as an efficient method for pneumonia diagnosis. Numerous researchers are dedicated to enhancing pneumonia diagnostic capabilities through artificial intelligence methods. This study employs a convolutional neural network (CNN) for pneumonia diagnosis. The dataset used in this study consists of chest X-ray images of healthy individuals as well as those affected by bacterial and viral pneumonia. In this study, a CNN model is implemented using an imbalanced chest X-ray dataset with a weighted cross-entropy cost function. The outcome of the developed CNN model shows an accuracy of 75.84%, a precision of 83.16%, a recall of 68.37%, and an F1 score of 68.97% on the test dataset. Further tuning of the model's hyperparameters is necessary to improve performance metrics.

Keywords: Pneumonia Diagnosis;Deep Learning;Chest X-Rays;Convolutional Neural Networks;Medical Imaging

1 Introduction

According to the World Health Organization (WHO), pneumonia is the single largest infectious cause of death in children worldwide. Therefore, an effective and immediate pneumonia detection mechanism is essential. Given that X-ray images serve as the primary diagnostic tool for pneumonia, the development of an automatic detection mechanism using X-ray images is important. Such an advancement would significantly enhance treatment efficacy and ultimately save countless lives that might otherwise be lost due to delays or errors in disease detection. Transmission of pneumonia typically occurs through inhalation of contaminated air, particularly in unhygienic or polluted environments. High-risk groups include young children and older adults above age 60, especially in cases of community-acquired pneumonia. The incidence of pneumonia varies by country, age, and gender, and is higher in male individuals aged above 65 years [1]. With the development of imaging modalities like X-ray and CT, examinations related to diagnosing different respiratory diseases can be performed at a much faster rate. Despite the increased utilization of CT, which has enhanced the early detection of severe clinical manifestations in patients, X-ray remains the primary choice for clinical screening and imaging follow-up due to its simplicity, speed, and cost-effectiveness. Moreover, it is the prevailing examination method for chest diseases currently. The manifestations of pneumonia on chest radiographs typically involve thickening and blurring of early lung markings [2], along with decreased lung transparency.

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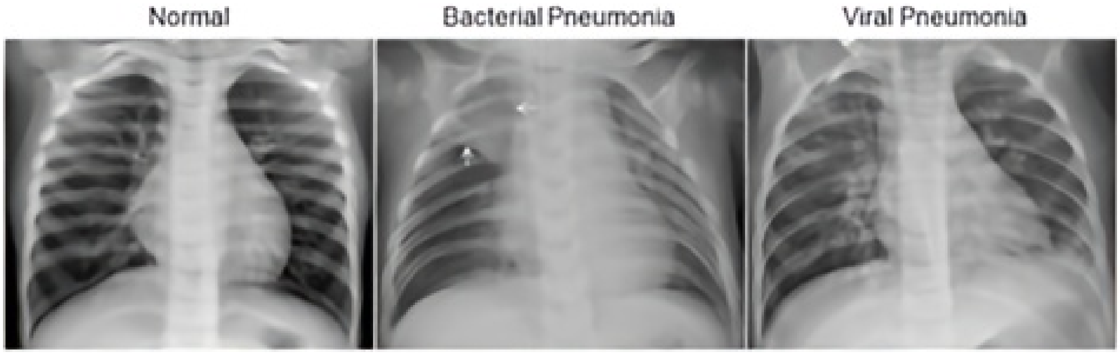

Figure 1: Examples of Chest X-Rays in Patients with Pneumonia extracted from the work of [3], which is the dataset used for this study.

As information and computer technology continue to advance, the use of image digitization and automatic recognition has become widespread across various sectors. This progress facilitates the extraction of information from images, enabling radiologists to make rapid and efficient assessments. The X-ray images from the original study of the dataset used in this paper [3], illustrated in Figure 1, depict three different conditions: a normal chest X-ray (left panel) showing clear lungs without any abnormal opacification, bacterial pneumonia (middle panel) with focal lobar consolidation in the right upper lobe (white arrows), and viral pneumonia (right panel) with a more diffuse interstitial pattern in both lungs. The remainder of this paper is organized as follows: Section 2 provides a review of related works. Section 3 outlines the proposed methodology, including model architecture and details. In Section 4, the experiments are conducted, and the dataset and software are discussed in detail. In Section 5, the results are presented, and further, the limitations are discussed. Finally, the conclusion and future recommendations are presented in Section 6.

2 Related Work

Neural networks have been applied in various domains ranging from transport demand prediction [4] to medical imaging for disease diagnosis. These models, including Convolutional Neural Networks (CNNs), have proven effective in tasks like classification, segmentation, and feature extraction. Throughout history, machine learning has been utilized in various applications within the medical field, particularly in disease diagnosis and prediction tasks. In recent times, a large variety of algorithms suitable for disease diagnosis and prediction have emerged, covering a wide range of disease conditions, including neurological disorders such as Alzheimer's disease, Parkinson's disease, dementia, and epilepsy, as well as cardiovascular diseases, prostate cancer predictions (classifying malignant and benign tumors) [5], and many other common health conditions. The scope of deep learning is broad, and in recent years, there has been a notable transformation in medical image analysis due to the emergence of deep learning-based image analysis methods [6, 7]. Deep convolutional neural networks (CNNs), renowned for their effectiveness in image classification, segmentation, and feature extraction, have played an important role in advancing automated medical imaging systems. Utilizing deep CNNs for pneumonia detection has exhibited promising results. Recent research related to the use of deep learning in pneumonia diagnosis, especially since 2020, has focused mainly on detecting COVID-19-related pneumonia [8]. Many studies, such as [9, 10], have employed transfer learning and deep convolutional neural networks (CNNs) for this purpose. Some image classifications, like [11], were performed using the Support Vector Machine (SVM) algorithm and transfer learning models such as ResNet50, VGG16, and VGG19. Transfer learning with pre-trained models has increased the accuracy of recent X-ray image classification models. The work of [12] provides a comprehensive summary of recent models used in pneumonia detection. Several related studies have been conducted using the chest X-ray dataset employed in this paper. For example, the work of [13] proposes a transfer learning-based convolutional neural network using the same dataset. This proposed model by [13] achieved a test accuracy of 98.43% and an AUC score of 0.9976. The work of [14] utilizes two pre-trained models, EfficientNetB0 and DenseNet121, achieving an accuracy of 95.19%, a precision of 98.38%, a recall of 93.84%, and an F1 score of 96.06% on the test dataset for detecting pneumonia. This model is trained using a similar X-ray dataset as in this study.

3 Proposed Method

The schematic of the Convolutional Neural Network (CNN) model used in this study for the binary classification of X-ray images into Normal and Pneumonia classes is shown in Figure 2. As shown in Figure 2, the model contains three convolutional (Conv) layers used for feature extraction and two fully connected (FC) layers used for classification. In the first Conv layer, there are 64 output nodes, and the activation function used is ReLU. ReLU is applied per pixel and replaces all negative pixel values in the feature map with zero. The second and third Conv layers produce outputs of 128 and 256 nodes, respectively. The activation function used throughout the second and third Conv layers is also ReLU. The mathematical formula for the ReLU activation function is represented in Equation 1:

$$\text{ReLU}(x) = \max(0, x) \tag{1}$$

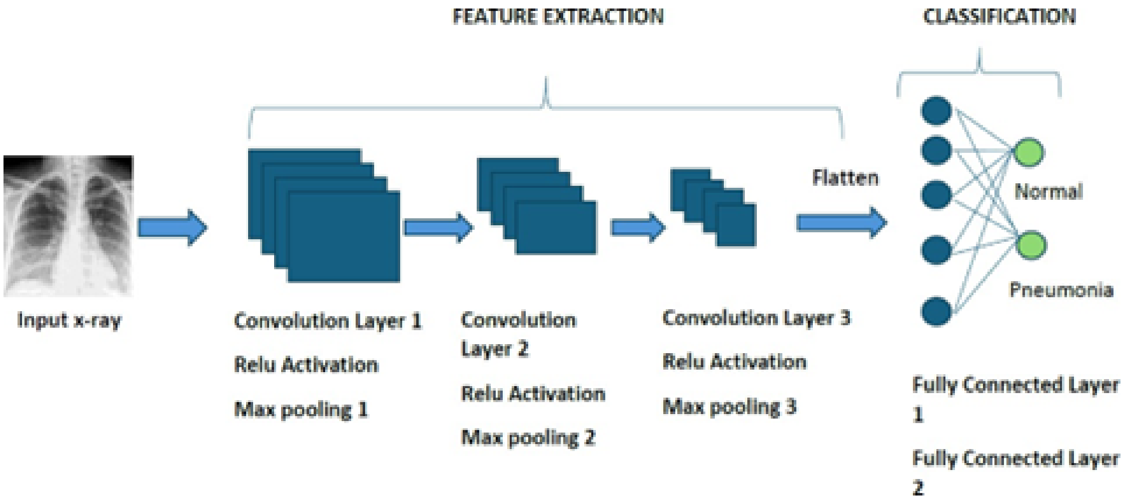

Figure 2: The schematic of the CNN architecture used in this study.

Dropout layers are not used in this model, although they can be included as part of future model development. Adding dropout layers could improve the model by randomly dropping out a percentage of nodes during operation, increasing randomness and potentially reducing overfitting. However, to keep the model computationally simpler, dropout layers were omitted, and the number of convolutional layers was limited to three.

4 Experiments

The experimentation process is carried out using PyTorch's `torch` library, and the adjusted dataset shown in Table 1 is used for training, validation, and testing of the model implemented in this study.

Table 1: The original dataset used for this study.

Dataset	**Number of Images**
Train (Normal class)	1341
Train (Pneumonia class)	3875
Validation (Normal class)	8
Validation (Pneumonia class)	8
Test (Normal class)	234
Test (Pneumonia class)	390
Total	**5863**

Additionally, for performance metric calculations, the `scikit-learn` library is utilized. The chest X-ray images are resized to dimensions of $224 \times 224 \times 3$, normalized to the range $[-1, 1]$, and transformed into tensors. Additional data augmentations such as cropping and rotations are not applied to maintain computational simplicity, given the limitations in GPU availability. The X-ray images are processed in batches. The dataset is visualized after the initial pre-processing, and a sample data visualization of a mini-batch of size 16 is displayed in Figure 3. The CNN architecture described in Figure 2 is utilized for feature extraction and classification. The loss function employed is weighted cross-entropy, and the optimizers used are Stochastic Gradient Descent (SGD) and Adam. The weight tensor of the cross-entropy loss used during the training of the model is calculated as shown in Equation 2:

$$\text{Weight of a class} = \frac{\text{Number of data instances of the class in the training dataset}}{\text{Total number of data instances in the training dataset}} \times \text{Number of classes} \tag{2}$$

Accordingly, weights of 1.92 and 0.67 are utilized for the 'Normal' and 'Pneumonia' classes, respectively, during the training of the model. Due to limited GPU availability, extensive hyperparameter tuning could not be performed during this study. However, some parameter tuning was conducted, and better performance was observed with the hyperparameter combinations shown in Table 3. The best-performing model was obtained with a learning rate of 0.1, a batch size of 32, and a convolutional kernel size of 3x3 using the SGD optimizer.

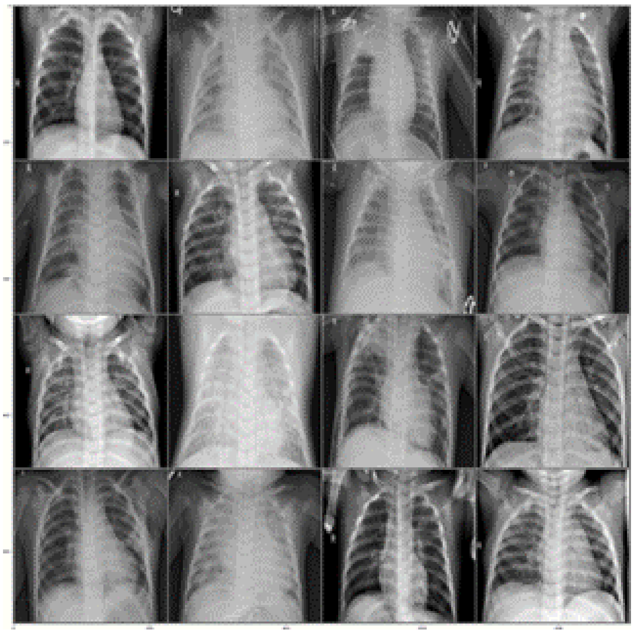

Figure 3: Sample chest X-ray images in a mini-batch of size 16 from the training dataset.

4.1 Dataset

The original dataset was downloaded from Kaggle[1]. The chest X-ray pneumonia dataset contains a total of 5863 X-ray images, arranged in three folders (train, test, validation), each containing subfolders for two categories: 'Pneumonia' and 'Normal.' The X-ray images were selected from retrospective cohorts of pediatric patients aged one to five years from Guangzhou Women and Children's Medical Center, Guangzhou. As per the dataset provider, all chest X-ray imaging was performed as part of patients' routine clinical care. For quality control, all chest radiographs were initially screened to remove low-quality or unreadable scans. The diagnoses for the images were graded by two expert physicians before being cleared for training the AI system, with a third expert reviewing the evaluation set to account for any grading errors. The original dataset is summarized in Table 1, mentioned earlier. The validation folder contained only a few data instances, so the training and validation datasets were rearranged into an 80/20 ratio. The adjusted dataset, used for this study, is presented in Table 2.

Table 2: The adjusted dataset used for this study.

Dataset	**Number of Images**
Train (Normal class)	1080
Train (Pneumonia class)	3104
Validation (Normal class)	271
Validation (Pneumonia class)	780
Test (Normal class)	234
Test (Pneumonia class)	390
Total	**5859**

4.2 Software and Hardware

The Google Colab platform and Jupyter Notebooks serve as the primary tools for editing and executing the Python code related to this study. The GPU provided by Google Colab is utilized for model execution, and as a result, the model's hyperparameters are kept computationally simple to accommodate the available resources. Despite these constraints, deep learning models require significant computational resources, particularly for operations like matrix multiplication, which is a core component of CNNs. As shown in studies on compiler optimization [15], improvements in matrix multiplication efficiency can significantly enhance neural network performance. However, due to the limited GPU availability in this study, the current model implementation remains constrained in terms of computational efficiency and the number of convolutional layers. Additionally, the Miniconda environment installed on a local device is employed for specific editing and visualization tasks, such as data augmentation and result interpretation. Future improvements to the computational setup could further enhance model training, such as integrating matrix multiplication optimizations or using more advanced hardware configurations.

[1] https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

Table 3: The combinations of hyperparameters that displayed better performance on the testing dataset.

Hyperparameter Combinations	**1**	**2**	**3**
Number of Training Iterations	20	20	20
Learning Rate	0.1	0.01	0.1
Weight Decay of Optimizer	0	0	0.1
Optimizer Type	SGD	SGD	Adam
Kernel Size of Conv Layer	3x3	3x3	5x5

5 Results and Discussion

The best performance is observed on the testing dataset at a learning rate of 0.1. The best-performing model is trained using hyperparameter combination 1, as displayed in Table 3. The relevant code and the saved model can be accessed via footnote[2]

All the results presented in this section are obtained from the best-performing model. Figure 4 shows the variation in training and validation accuracy during the training iterations. After 15 epochs, the model starts to slightly overfit the training data. Hence, the optimal number of training epochs for the model developed in this study lies between 15 and 20 epochs.

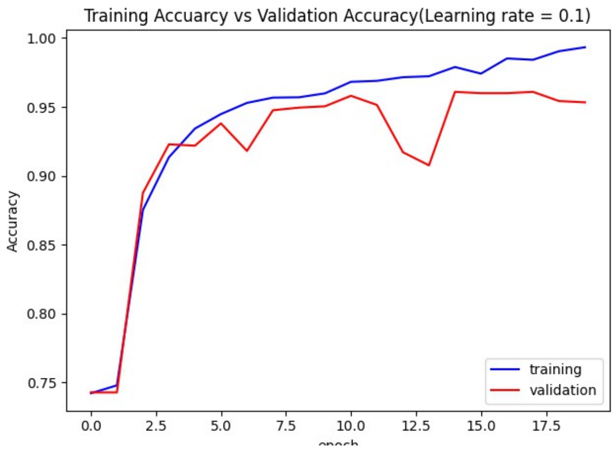

Figure 4: Variation of training and validation accuracy for the model at learning rate = 0.1, number of iterations = 20, weight decay = 0, and optimizer type = SGD.

The performance metrics of the model on the validation and testing datasets are shown in Tables 4 and 5, respectively. The training and validation accuracies of the model are 97.89% and 96.09%, respectively. The testing accuracy is comparatively lower at 75.84%. This indicates that the model has not fully captured the characteristics of the dataset yet.

Table 4: Performance of the model on the validation dataset.

Performance Metric	**Output**
Accuracy	96.09%
Precision	95.34%
Recall	93.34%
F1 Score	94.83%

Table 5: Performance of the model on the testing dataset.

Performance Metric	**Output**
Accuracy	75.84%
Precision	83.16%
Recall	68.37%
F1 Score	68.97%

The confusion matrices for the validation and testing datasets are shown in Figures 5 and 6, respectively. The confusion matrix for the testing dataset shows that the model is biased toward the 'PNEUMONIA' class, which is the majority class in the dataset. While the weighted cross-entropy function has managed to address class imbalance during training, the model

[2]The code and saved model can be requested from the corresponding author.

still exhibits an effect from this imbalance. This suggests that the weight tensor used could be erroneous and may require adjustments in future implementations. Additionally, other methods of addressing class imbalance, such as SMOTE or class balancing, could also be considered in future work.

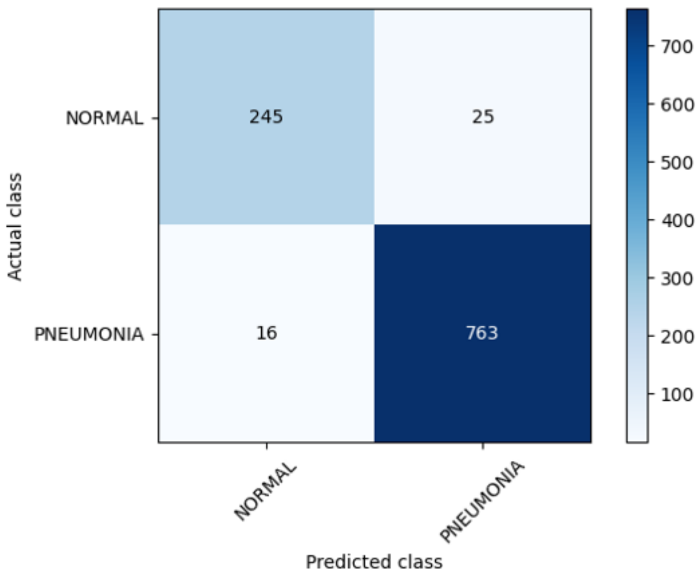

Figure 5: Confusion matrix for the validation dataset.

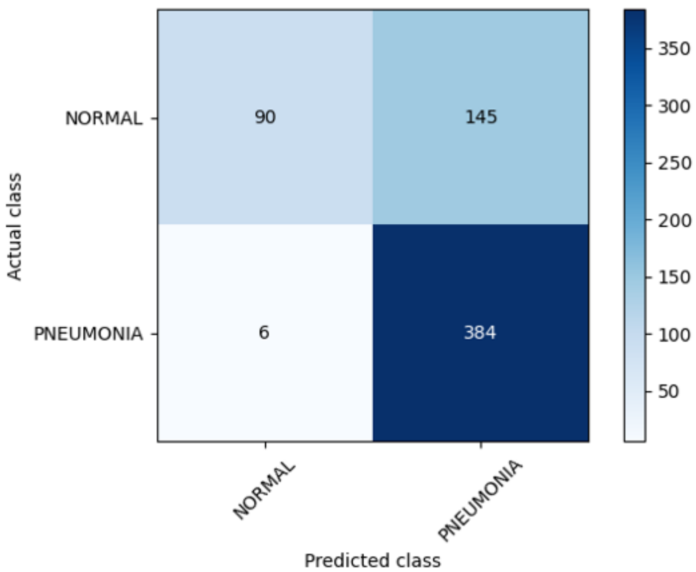

Figure 6: Confusion matrix for the testing dataset.

6 Conclusions and Recommendations

The performance metrics indicate that the CNN model developed in this study demonstrates better classification results on the validation data but fails to exhibit similarly strong performance on the test data. Furthermore, it is evident that the imbalanced nature of the dataset has impacted the final results, despite the use of a weighted cost function during model training. Due to limited GPU availability, the CNN model is constrained by the restricted number of convolutional layers, and no additional data augmentations were applied to the dataset. These factors have also contributed to the relatively low performance of the CNN model on the test dataset. Therefore, the current model is not suitable for clinical applications at this stage of training. Further optimization of hyperparameters is expected to improve performance metrics in future iterations. Additionally, enhancing the model architecture by increasing the number of convolutional layers and incorporating dropout layers could potentially yield better results. Exploring appropriate data augmentations is another possibility for future improvements. A significant enhancement to the model's performance can be achieved through transfer learning, using pre-trained models such as VGG19, ResNet50, or Inceptionv3. By fine-tuning these models for the specific task of pneumonia detection, the network can leverage features learned from vast datasets and adapt them to the current dataset. This approach not only enhances classification accuracy but also reduces the computational burden and training time required. Hence, the use of transfer learning presents a promising avenue for future improvements to the CNN models in this study.

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Declaration of Competing Interests

The author declares no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

Ayesha Karunaratna Mudiyanselage: Conceptualization, Methodology, Data Analysis, Writing - original draft, review, and editing.

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Innovative Strategies in Lean Supply Chain Management: Enhancing Efficiency in Healthcare

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Abstract

In the ever-evolving healthcare landscape, integrating Lean principles into supply chain management has emerged as a crucial strategy for enhancing efficiency and resource allocation. This paper explores recent advances in Lean Supply Chain Management (LSCM) within the healthcare sector and presents innovative strategies to optimize resource allocation. Synthesizing existing literature and case studies elucidates the principles of Lean thinking and their application to healthcare supply chains. Key topics addressed include waste reduction, process optimization, inventory management, and collaboration among stakeholders. Additionally, the role of technology and data analytics in streamlining supply chain operations is investigated. Furthermore, the paper delves into challenges and potential barriers to implementing LSCM in healthcare settings, along with recommendations for overcoming them. A comprehensive analysis of current trends and practices provides valuable insights for healthcare organizations seeking to enhance efficiency and effectiveness in their supply chain management practices.

Keywords: Lean Thinking; Healthcare Supply Chain; Efficiency; Resource Optimization; Technology Integration

1 Introduction

Lean Supply Chain Management (LSCM) is a business approach that integrates lean methods and principles throughout the supply chain to achieve world-class business performance [1]. It entails implementing lean concepts such as waste reduction and continuous improvement to maximize effectiveness and flexibility across the entire supply chain [2]. LSCM strives for continual improvement and waste elimination to enhance client value, speed, and quality. It is necessary to integrate lean principles throughout the supply chain to achieve significant improvements in performance [3]. Operational aspects, planning, and strategy implementation are prioritized in LSCM [2]. Unlike traditional supply chain management, which emphasizes control and pressure on partners, LSCM focuses on improving revenue and collaboration among partners [4]. The goals of LSCM are to examine supply chain operations across numerous organizations, simplify planning processes, and improve agile synchronization and variability management in global supply chains [5]. Implementing LSCM can lead to reduced expenses, greater operational performance, and increased corporate competitiveness, especially in the context of technological uncertainty [6]. Benefits such as better quality, faster delivery, and increased supply chain profitability could result from this, coupled with decreased costs and waste [7]. However, some LSCM efforts may face more challenges than others depending on the anticipated performance increase, and implementation tactics that are ill-considered can compromise the success of these programs [8]. Moreover, there may be difficulties in implementation, as each bundle of LSCM methods may not always produce the desired result.

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Lean management in the healthcare sector aims to reduce costs without sacrificing care quality [9]. Lean methodologies have been shown to significantly improve quality, efficiency, and safety in healthcare settings while using fewer resources [10]. Lean management can elevate the standard of patient care by enhancing clinical outcomes in a significant and lasting manner. The goal of lean healthcare is to maintain a hospital's financial stability while delivering excellent treatment to patients in an efficient, effective, and responsive manner [11]. Lean initiatives have resulted in benefits such as shorter wait times, cost savings, fewer errors, and higher levels of staff and patient satisfaction [12]. Better work environments, increased asset utilization, and higher patient satisfaction are potential outcomes of lean management in the healthcare industry [13]. Despite its growing popularity, there are still opportunities and challenges for organizations seeking to apply lean management principles in this sector [14]. Healthcare supply chains face specific challenges. Unlike manufactured goods, healthcare products must meet certain standards; thus, safe transportation is crucial. Precise planning, accurate demand forecasting, and efficient product distribution are essential for maintaining a successful healthcare supply chain [15]. While much research has been conducted on challenges such as inventory management and technology utilization, two areas that still need attention are personnel training and drug tracking [16]. Moreover, the COVID-19 pandemic exposed gaps in the healthcare supply chain, leading to delays and shortages [17]. To overcome these challenges, improved supply chain management is essential, which involves diversifying suppliers and implementing safety measures [18]. In the future, the adoption of global best practices and the formation of stronger alliances will shape the healthcare industry [19].

There have been significant turning points in the development of lean principles within the healthcare industry, showing how these ideas have been adapted and applied in this context. Similar demands in the healthcare sector during the 1990s led to the adoption of lean concepts [20]. Lean ideas such as "pull," controlling process flow, mapping value streams, defining value from the customer's perspective, and striving for perfection were eventually introduced and implemented in healthcare settings [21]. Since then, improvements in patient wait times, emergency department throughput, and bedside rounding procedures have been observed, ultimately contributing to an enhanced standard of medical care [22]. Technological developments are transforming supply chain management practices in the healthcare sector. The use of integrated information technology systems enables the adoption of lean and reverse logistics techniques, both of which are critical for improving healthcare delivery [23]. These solutions enhance quality, visibility, speed, and cost-effectiveness across the supply chain. Furthermore, smart technologies are being applied in novel supply chain applications to minimize waste and quickly respond to demand fluctuations [24]. Efficient healthcare supply chain management, which reduces waste and boosts operational performance, requires the integration of information technology and digitization [25]. Additionally, healthcare supply chains are gradually embracing circular economy principles to incorporate sustainable planning methods and reduce resource consumption [26]. Lean manufacturing concepts are gaining traction in the healthcare sector, albeit to varying degrees. These methods offer opportunities for cost reduction and higher-quality care [27].

2 Background of LSCM in Healthcare

Lean Supply Chain Management (LSCM) has evolved beyond being merely a set of methods and tools aimed at cost reduction [28]. The current focus is on adding value [29] by combining traditional lean techniques with various soft practices, including leadership, respect for people, kata, and dedicated management [30, 31]. Figure 1 illustrates the core principles of LSCM.

Figure 1: Core Principles of Lean Supply Chain Management

Lean SCM encompasses the following principles [28, 32, 33]:

- Identifying value from the customer's viewpoint.

- Finding and eliminating waste in the supply chain.
- Maintaining an uninterrupted value flow.
- Implementing a pull system to deliver supplies on schedule.
- Striving for excellence through continuous improvement.

The Toyota Production System, developed by the Japanese automaker Toyota, laid the foundation for Lean Healthcare Practice (LHP). Lean concepts, initially created for manufacturing processes, later found applications in other sectors, including industrial services and the public sector. As hospitals are integral to the healthcare system, many are adopting lean approaches to enhance efficiency and streamline operations [34]. The healthcare sector's shift towards process optimization and waste reduction reflects the adaptation of lean principles to its unique challenges. The fundamental lean principles of standardization, inventory reduction, and process improvement are aligned with the specific needs of healthcare organizations [35]. Lean's introduction into healthcare originated from its application in manufacturing to address inefficiencies such as long wait times in Canada's public healthcare system. In 2008, organizations like the Five Hills Health Region, St-Joseph's Health Center, and St-Boniface Hospital began experimenting with lean concepts, sparking formal discussions about the approach in Québec. In 2011, the Québec Ministry of Health and Social Services implemented lean principles across the province's healthcare network, with later phases extending the program to other organizations [36]. These efforts, through lean approaches, aimed to improve stakeholder satisfaction, quality of care, accessibility, and efficiency.

Table 1: Comparative Analysis of Lean Implementation: Healthcare vs. Manufacturing Sector

Aspect	**Healthcare Sector**	**Manufacturing Sector**
Nature of Operations	Close interaction with patients; customer-focused lean effectiveness; requires flexible, quick responses along multiple flow paths involving patients.	Focus on production processes; efficiency in production lines; emphasis on standardization and consistency.
Challenges and Pressures	Aging population, chronic diseases, rising costs; similar pressures as manufacturing faced in the 1990s.	Competitive market, cost reduction, improving production efficiency.
Application of Lean Tools	Involves mapping process flow, waste removal, and inventory optimization tailored to healthcare settings.	Utilizes traditional lean tools like 5S, Kanban, and continuous flow to optimize manufacturing processes.
Success Factors	Organizational leadership, employee knowledge about lean, training, patient satisfaction; crucial to educate and involve physicians in continuous improvement.	Strong management support, employee training, clear goals, and metrics for improvement.
Barriers	Resistance from healthcare practitioners, lack of lean knowledge among staff, complexity of healthcare processes.	Resistance to change, existing process inertia, initial cost of lean implementation.

The adoption of lean principles in the healthcare industry has produced significant results, particularly in terms of improving patient care and operational efficiency. Previous studies have reported positive outcomes, such as shorter hospital stays, reduced wait times, and enhanced accessibility to care. Furthermore, lean initiatives have been shown to boost operational performance, reduce costs, increase productivity, and optimize capacity in healthcare organizations [37]. Additionally, lean methods have fostered a positive work environment, motivated healthcare staff, and cultivated a culture of continuous improvement, leading to enhanced care and service quality for patients [38].

3 Recent Advances in Lean SCM in Healthcare

Recent developments in the healthcare industry's Lean Supply Chain Management (SCM) emphasize the importance of technological breakthroughs. Hospital supply chains can undergo a revolution due to the transformative techniques of big data analytics and artificial intelligence (AI). These systems help reduce waste and minimize supply shortages by prioritizing tasks such as inventory management, demand forecasting, and procurement [39]. Apart from technological advancements, Lean SCM has focused significantly on the integration of data analytics and predictive modeling. Predictive analytics is a crucial tool for improving decision-making and overall performance, and it is applied to optimize supply chain operations [40].

Moreover, the implementation of machine learning and sophisticated forecasting methodologies has played a pivotal role in mitigating inefficiencies in inventory management and demand forecasting in public healthcare systems. As a result, medication access and resource allocation have seen noticeable improvements [41]. Figure 2 illustrates the recent advances in Lean SCM in Healthcare.

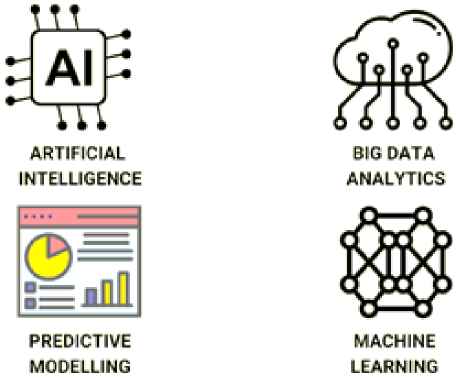

Figure 2: Recent Advances in Lean SCM in Healthcare

Research has shown significant positive correlations between supply chain innovation and lean healthcare practices. Lean approaches have been found to have a direct impact on enhancing supply chain innovation initiatives, highlighting the significance of lean approaches in fostering innovation in healthcare supply chains [42]. Furthermore, the major effect of predictive analytics on perceived profits and performance in supply chain management is emphasized [43], reinforcing the necessity of predictive analytics to streamline supply chain processes. AI improves the effectiveness of the supply chain by enabling data-driven decision-making. AI systems provide real-time insights that optimize inventory control, logistics, and procurement processes, resulting in lower costs and more efficient operations [44, 45]. AI algorithms process large volumes of data from diverse sources. Automated solutions, such as robotic process automation (RPA), reduce human error and enhance operational efficiency by handling repetitive tasks. Automation is another key component of AI technology. For instance, medical supply availability can be ensured on time with the help of automated order processing and inventory tracking, which drastically reduces processing times. One of the primary advantages of AI in healthcare supply chains is its enhancement of predictive analytics. To effectively estimate demand, AI and machine learning algorithms evaluate past data, seasonal trends, and external variables. This approach maintains optimal inventory levels and prevents stockouts or overstocks. Furthermore, AI systems provide insights into patient behavior and healthcare consumption patterns, aiding in forecasting future demand for specific drugs or medical supplies, ensuring that supply chains are prepared to meet patient needs [46].

AI-driven systems are crucial for resilience and disruption management during crises, such as pandemics, as they can quickly adjust to changing conditions by analyzing real-time data and developing contingency plans. Additionally, big data analytics help monitor and analyze various factors, such as vendor performance, geopolitical events, and logistical challenges, thereby improving supply chain resilience and responsiveness [47]. Machine learning algorithms can also identify potential disruptions in the supply chain and suggest alternative strategies to mitigate risks. AI further facilitates coordination and collaboration among stakeholders in the healthcare supply chain. AI-enabled game-theoretic models determine optimal pricing, profit-sharing, and innovation strategies, promoting collaboration and efficient resource allocation between manufacturers, suppliers, and healthcare providers. Integrated AI-powered platforms simplify supply chain management by ensuring seamless information exchange, coordination, transparency, and synchronization [48]. Finally, AI supports healthcare supply chains in their sustainability initiatives. AI leads to significant cost savings and economies of scale through waste reduction, productivity enhancement, and resource optimization. Additionally, AI-driven analytics can identify opportunities to reduce the environmental impact of supply chain operations, such as through sustainable sourcing practices and optimizing transportation routes to reduce carbon emissions [49].

4 Successful Implementation of Lean Supply Chain Management: Case Studies

Healthcare organizations around the world face constant challenges in maintaining cost-effectiveness while improving operational efficiency. This section highlights case studies where Lean Supply Chain Management (LSCM) has been successfully implemented.

4.1 Caldwell UNC Healthcare

This case study examines how Caldwell UNC Healthcare, a community hospital in North Carolina, successfully implemented Lean Supply Chain Management (LSCM), leading to significant cost reductions and operational improvements [50]. Facing the ongoing challenge of rising healthcare costs, Caldwell UNC Healthcare realized the necessity of streamlining its supply chain management processes. The hospital partnered with Simpler Consulting to integrate lean principles into their supply chain operations. The initial step involved a thorough evaluation of the hospital's supply chain, identifying substantial opportunities for improvement, particularly in employee productivity and inventory management. The success of this initiative was largely due to the active involvement of frontline workers, including doctors, nurses, and medical technicians. Information was gathered through observational research, internal documents, and consultations. Cost data and inventory levels were derived from internal records, while consultations with Simpler Consulting provided insights on improving efficiency and managing inventories more effectively.

Observational studies of frontline personnel helped to highlight workflow and inventory management procedures. The BlueBin system was used to track inventory levels in real-time. Performance metrics were developed based on baseline assessments, utilizing historical data on spending, production, and inventory levels. Lean management tools such as value stream mapping and root cause analysis were employed to streamline processes and eliminate non-value-added activities. Employee engagement was analyzed through task completion times and feedback, while cost savings were assessed by comparing pre- and post-implementation data. Ongoing oversight ensured long-term benefits and identified additional areas for savings. Triangulation ensured a comprehensive understanding of the process, with active participation from both frontline staff and management. Quantitative and qualitative analyses were conducted, examining employee feedback and cost reductions. Caldwell UNC implemented the following key strategies to achieve their objectives:

- **Inventory Management Optimization:** The hospital prioritized improving inventory utilization and eliminating excess inventory in all clinical departments. Through process redesign and collaboration with frontline workers, immediate efficiency gains were realized.
- **Visual Inventory Management Dashboard:** The implementation of the BlueBin system provided real-time visibility into inventory levels, empowering clinicians to make informed decisions. This data-driven approach enabled staff to optimize inventory management effectively.
- **Employee Productivity Enhancement:** By applying lean principles, the hospital optimized staff responsibilities and streamlined processes. Caldwell UNC was able to reduce labor-intensive tasks and increase productivity by redistributing work and leveraging the skills of its employees.

As a result of implementing LSCM, Caldwell UNC Healthcare achieved significant cost reductions. Over five months, the hospital realized savings of $2.62 million, with additional savings from reduced resource consumption and distribution costs. The development of employee empowerment and engagement greatly contributed to maintaining improvements across the organization. Despite the success of LSCM, Caldwell UNC Healthcare recognizes ongoing challenges, particularly in managing product pricing—especially in the pharmaceutical industry—and accommodating physician preferences amid technological advancements. The hospital remains committed to continuously improving its supply chain processes to further reduce healthcare costs and enhance patient care. The success of lean principles in healthcare supply chain management is evident from Caldwell UNC Healthcare's experience. The hospital achieved considerable cost savings and operational improvements through technology integration, active frontline worker participation, and a strategic focus on efficiency. This case study underscores the importance of proactive and strategic supply chain management to deliver high-quality, affordable healthcare services.

4.2 Sri Lankan Teaching Hospitals

The implementation of lean principles in Sri Lankan teaching hospitals aimed to increase efficiency, reduce waste, and raise the standard of patient care within the supply chain. The goal of this initiative was to enhance overall performance in the healthcare supply chain by identifying and eliminating activities that did not add value [51]. A methodical approach was adopted, combining both qualitative and quantitative techniques. Data were collected from 130 stakeholders, including physicians, nurses, medical laboratory technicians, radiographers, physiotherapists, pharmacists, medical students, and patients, through non-participant observations, interviews, and questionnaires. To evaluate current procedures and identify inefficiencies, lean tools such as Just-In-Time (JIT), Poka Yoke (error-proofing), continuous improvement (Kaizen), and value stream mapping were employed. Additionally, root cause analysis was conducted using RQDA analysis within the R studio environment. Lean implementation yielded notable improvements across several key areas. The Colombo South Teaching Hospital (CSTH) outperformed the Colombo North Teaching Hospital (CNTH) and the National Hospital of Sri Lanka (NHSL), with mean performance indicators ranging from 2.5 to 4.0. Major sources of waste identified included the unnecessary transfer of medications, frequent changes in the demand for medical supplies, and long lead times for various procedures. Operational improvements included enhanced workflow efficiency, reduced wait times, and fewer unnecessary supply movements. Costs were particularly reduced in the areas of prescription drugs and long-term care. This case study demonstrated the successful application of lean principles in the healthcare supply chains of Sri Lankan teaching hospitals. The implementation led to significant improvements in cost-effectiveness, service quality, and operational efficiency. The reduction in waste resulted in considerable cost savings, while better workflow and shorter patient wait times contributed to improved patient outcomes. The success of the CSTH initiative serves as a model for other hospitals, showcasing how Lean Six Sigma practices can be scaled and adapted to diverse healthcare settings.

5 Key Strategies for Lean Supply Chain Management in Healthcare

Key strategies for the success of Lean Supply Chain Management (LSCM) include streamlining inventory management to reduce waste, optimizing procurement processes to ensure timely and cost-effective sourcing of medical supplies, and fostering strong supplier relationships to enhance collaboration and reliability. Leveraging technology for real-time data analytics can enhance decision-making and responsiveness, while continuous process improvement initiatives, such as Kaizen, can help identify and eliminate inefficiencies. By adopting these strategies, healthcare organizations can create a more agile, cost-effective, and patient-centered supply chain. Figure 3 represents the key strategies necessary for the success of LSCM in healthcare.

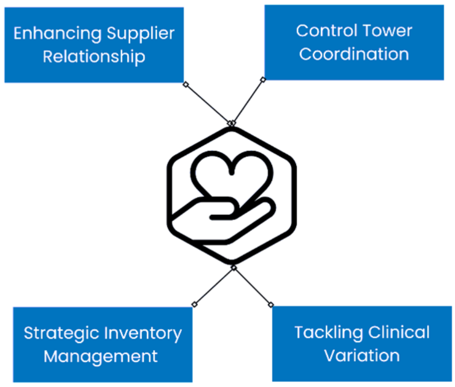

Figure 3: Key Strategies for Lean Supply Chain Management in Healthcare

5.1 Inventory Management Strategies

Effective inventory management is essential in the healthcare industry because it impacts both patient care and operating expenses [52]. Proper inventory management is vital to ensuring that patients receive timely, high-quality care while simultaneously reducing costs [53]. Challenges such as overstocking or shortages of supplies, particularly during crises like the COVID-19 pandemic, underscore the importance of efficient inventory management. Various approaches and methodologies, such as Economic Order Quantity (EOQ), Mathematical Optimization Models, and Metaheuristics, have been developed to model hospital inventory management effectively [54]. Furthermore, healthcare facilities are encouraged to integrate modern technologies such as artificial neural networks and radiofrequency identification (RFID) to optimize inventory control [52, 53]. Key inventory control methods in healthcare include ABC, VED, FSN, and SDE analyses [53]. However, several challenges exist in implementing inventory management systems in healthcare, including inaccurate data, poor staff training, and a lack of consistency. Despite these difficulties, a thorough understanding of the unique needs and challenges faced by healthcare facilities is crucial for successful implementation [52].

5.2 Just-in-Time (JIT) Inventory Systems Strategies

Implementing Just-in-Time (JIT) inventory methods is crucial for reducing waste and preventing overstocking in healthcare supply chains. By ordering and receiving supplies only when they are needed, healthcare facilities can significantly reduce costs and improve patient care. This can be achieved through close collaboration with suppliers and the use of technological solutions [51]. JIT inventory management has introduced a revolutionary approach to improving organizational efficiency and patient care in healthcare supply chain management. Research has demonstrated that JIT effectively reduces waste and enhances service quality, leading to observable savings in operating expenses [55]. Comparative studies highlight the superiority of organizations that adopt JIT, underscoring the critical role JIT plays in improving overall performance [56]. However, it is essential to acknowledge the risks associated with JIT, particularly concerning supply chain disruptions, which require careful planning and risk mitigation strategies [57]. By applying JIT principles, healthcare institutions can navigate the complexities of the healthcare landscape, streamline processes, allocate resources more efficiently, and ultimately improve patient outcomes.

5.3 Collaboration and Partnership Strategies

Collaboration and partnership strategies are essential to Lean Supply Chain Management (LSCM) in healthcare as they promote efficiency and integration [57]. These strategies enable seamless coordination between hospitals and suppliers through cooperative planning, execution, and decision-making processes. Decisions related to suppliers and partnerships are critical because collaborative partnerships offer benefits such as resource access and risk sharing [58]. Furthermore, a cost-benefit sharing framework highlights the importance of cooperation in reducing costs, managing risks, and enhancing performance [59]. Successful collaboration is ensured through the equitable distribution of costs and rewards among stakeholders, fostering mutual gains.

Increasing cooperation among stakeholders—including suppliers, physicians, and administrators—is crucial to optimizing inventory control and achieving efficiency in healthcare supply chain management. Collaborative initiatives, such as vendor-managed inventory (VMI) programs and strategic alliances, facilitate precise inventory monitoring, timely replenishment, and cost-effective resource allocation, ultimately leading to improved patient outcomes and operational performance [51].

5.4 Demand Forecasting and Capacity Planning Strategies

Accurate demand forecasting and capacity planning are vital for the efficient allocation of resources in healthcare settings. By utilizing data analytics tools to predict demand patterns, healthcare organizations can improve operational efficiency and cost-effectiveness by optimizing inventory levels and ensuring timely resource availability [51]. Table 2 illustrates how various strategies contribute to effective resource allocation in healthcare supply chain management.

Table 2: Strategies for Lean Supply Chain Optimization in Healthcare

Aspect	Description	Solution
Reducing Inventory and Shortage Costs	Demand forecasting errors lead to high inventory and shortage costs [60].	Utilize artificial neural networks for accurate demand forecasting to minimize costs [60].
Improving Medication Ordering	Accurate demand estimation and agile delivery are essential [61].	Implement the Kanban system for accurate demand estimation and waste reduction [61].
Optimizing Supply Chain Configuration	Optimization driven by accurate demand forecasting enhances efficiency [15].	Optimize supply chain configuration and distribution based on precise forecasting [15].

6 Challenges and Barriers for Implementation of Lean SCM in Healthcare

Healthcare organizations face several obstacles when implementing Lean Supply Chain Management (SCM), including technological, regulatory, cultural, and financial challenges.

6.1 Technological Obstacles

Technological challenges to the adoption of Lean SCM include inadequate internet access, inconsistent infrastructure, and environmental unpredictability. While digitization and information technology are recognized as essential tools for improving medical supply chains, achieving an efficient supply chain remains difficult without a robust technological foundation [62].

6.2 Regulatory Obstacles

Regulatory hurdles significantly impact the coordination of supply chains in healthcare. These regulatory concerns, along with the unique characteristics of the healthcare network, have a considerable influence on the effectiveness of healthcare SCM activities [63, 64].

6.3 Cultural Challenges

Cultural factors within healthcare organizations—such as corporate culture, leadership, and employee involvement—play a critical role in the success of lean healthcare initiatives [59]. Additionally, issues related to professionalism, implementation fidelity, and the demand for evidence-based research complicate the implementation and sustainability of Lean SCM in healthcare settings [65].

6.4 Financial Challenges

Financial constraints are a significant barrier to the implementation of Lean SCM, particularly in the areas of skill development, ongoing maintenance, and adaptation to regulatory changes [66]. However, lean SCM projects provide healthcare organizations with the opportunity to address budgetary challenges by improving drug distribution systems, ensuring patient safety, optimizing instrument utilization, and managing supply chain costs more effectively [67]. Figure 4 highlights the challenges in implementing Lean SCM in healthcare.

6.5 Addressing Technological Challenges

Overcoming technological challenges requires a multi-faceted approach. Tools such as Fuzzy-AHP can prioritize efforts based on potential performance gains, ensuring effective resource allocation [68]. For system-wide Lean adoption, it is necessary to integrate social, technical, and external components, which ensures system compatibility [69]. Additionally, careful planning, input from healthcare professionals, and the integration of Industry 4.0 technologies—such as IoT, big data, and AI—alongside Lean methodologies improve operational performance [70]. Successful large-scale Lean deployments require completing transitional phases over several years, along with dynamic cross-case analysis, demanding perseverance and patience [71].

6.6 Addressing Cultural Challenges

Cultural resistance to lean concepts in healthcare can be mitigated through effective communication, collaboration strategies, and an understanding of organizational transformation via models like the "contingent Lean culture adoption" model [72]. Healthcare providers must address specific behavioral drivers of resistance [73]. Since organizational culture heavily

Figure 4: Challenges in Implementing Lean SCM in Healthcare

influences lean implementation, targeted strategies to reduce defensive mechanisms are essential [74]. Integrated and coordinated efforts—such as robust change management and employee involvement—are key to successfully implementing lean principles [69].

6.7 Addressing Regulatory Challenges

Several best practices are crucial for overcoming regulatory barriers to Lean SCM implementation in healthcare. Customizing terminology and symbols to fit a patient-centered approach ensures effective communication and regulatory compliance. Clear communication and employee incentives help overcome resistance from practitioners and ensure adherence to regulatory standards [75]. Lean initiatives can remain compliant through strong leadership and comprehensive training programs [76]. Identifying facilitators such as organizational shortcomings and barriers like a lack of awareness and inadequate support aids in navigating regulatory complexities [77]. A practice-driven methodology, initiated by strategic planning and sustained through ongoing improvement efforts, systematically addresses regulatory obstacles [78].

6.8 Addressing Financial Challenges

Several practical strategies can be employed to overcome financial obstacles to Lean SCM implementation in healthcare. Adopting patient-centered terminology and symbols streamlines processes and reduces costs associated with misunderstandings and inefficiencies [74]. Clear communication and motivating healthcare practitioners help minimize resistance, maximize resource utilization, and reduce implementation costs [74]. Competent leadership and thorough training prepare the workforce for Lean interventions, reducing the risk of errors and costly rework [76]. Financial challenges can be systematically addressed by identifying organizational inadequacies and obstacles, such as a lack of support and knowledge gaps, while ensuring optimal resource allocation through strategic planning and continuous improvement programs [77, 78].

7 Future Directions and Opportunities for Lean SCM in Healthcare

The future trajectory of Lean Supply Chain Management (SCM) in healthcare is poised for significant advancements driven by technological innovation, strategic partnerships, and enhanced operational efficiencies. Building upon current trends, several key areas emerge as critical for shaping the future landscape of Lean SCM:

- **Global Standardization and Scalability:** Global standardization of Lean SCM frameworks will be essential for facilitating benchmarking and scalability across diverse healthcare systems [79]. By implementing standardized processes, healthcare organizations can improve quality and efficiency consistently, while adapting more easily to various operational and regulatory environments. This standardization will also foster cross-border collaboration and the exchange of best practices, promoting continuous improvement on a global scale.

- **Expansion into Outpatient and Community Healthcare:** Expanding Lean SCM principles beyond traditional hospital settings to outpatient clinics and community healthcare centers presents a significant opportunity [80]. By implementing Lean approaches in decentralized care environments, healthcare organizations can optimize resource allocation, streamline supply chain operations, and increase patient access to essential medical supplies and services. Tailored Lean solutions will drive efficiency across the continuum of care, with a focus on patient-centricity, agility, and flexibility in outpatient care.

- **Integration of Advanced Technologies:** The integration of advanced technologies, such as artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT), will redefine Lean SCM practices in healthcare [81]. AI and ML algorithms can transform inventory control and demand forecasting accuracy, enabling proactive risk management and real-time decision-making. IoT-enabled devices will enhance supply chain visibility and traceability, ensuring timely replenishment and reducing waste. Additionally, big data-driven predictive analytics will optimize distribution and logistics networks, improving overall operational resilience and efficiency.

- **Collaboration Across the Healthcare Ecosystem:** Collaboration will be paramount in future Lean SCM initiatives, fostering seamless integration and coordination across the healthcare supply chain ecosystem [82]. Strategic alliances between hospitals, insurance providers, drug manufacturers, and equipment suppliers will streamline procurement processes, promote price transparency, and reduce supply chain risks. Joint efforts, such as vendor-managed inventory (VMI) programs and shared logistics platforms, will enhance supply chain responsiveness and resilience, ensuring uninterrupted services in times of disruption.

- **Enhanced Quality Metrics and Performance Measurement:** Future Lean SCM strategies will prioritize comprehensive quality metrics that extend beyond traditional measures to encompass patient outcomes, safety, operational efficiency, and cost-effectiveness [79]. Sophisticated performance measurement tools will enable healthcare organizations to assess the overall impact of Lean initiatives and identify areas for targeted improvement. Data-driven insights and continuous feedback loops will drive the pursuit of ongoing improvement, ultimately enhancing patient satisfaction and healthcare delivery.

- **Resilience and Adaptive Strategies:**

  Building resilience into Lean SCM practices will be critical for mitigating risks posed by global disruptions and healthcare crises [83]. Future initiatives will emphasize adaptive logistical frameworks, flexible sourcing strategies, and comprehensive contingency planning. By implementing multi-grade fuzzy logic and scenario planning methodologies, healthcare organizations will enhance supply chain agility and preparedness, allowing them to respond quickly to unforeseen challenges while maintaining lean principles of efficiency and waste reduction.

- **Innovation in Waste Reduction and Process Optimization:**

  Innovation will continue to drive waste reduction and process optimization in healthcare supply chains [79]. By combining Kaizen events with Lean Six Sigma methodologies, healthcare organizations can foster a culture of operational excellence and innovation. Embracing digital transformation efforts and emerging technologies will further maximize workflow efficiency, automate repetitive tasks, and eliminate non-value-added activities. This unwavering focus on innovation will enable healthcare organizations to deliver high-quality care affordably while adapting to changing patient needs and market dynamics.

- **Sustainability and Ethical Sourcing:** Long-term sustainability and ethical sourcing practices will increasingly shape Lean SCM strategies in healthcare [79]. Healthcare organizations will prioritize partnerships with suppliers committed to social responsibility and environmental stewardship. Sustainable procurement strategies, such as green logistics and circular economy principles, will reduce environmental impact and maximize resource efficiency.

By incorporating sustainability into Lean SCM frameworks, healthcare organizations can enhance their brand reputation, minimize regulatory risks, and contribute to global health and environmental goals. The future of Lean SCM in healthcare is bright, driven by strategic partnerships, technological innovation, and a commitment to sustainability. By embracing these future directions—global standardization, technology integration, expansion into decentralized care, ecosystem collaboration, enhanced metrics, resilience strategies, innovation, and sustainability—healthcare organizations can achieve significant improvements in efficiency, cost-effectiveness, and patient outcomes. Continued research and the application of these advanced Lean approaches will be essential for navigating complexity and capitalizing on opportunities in healthcare supply chain management.

8 Conclusion

The implementation of Lean Supply Chain Management (LSCM) in the healthcare industry is a transformative strategy that enhances operational efficiency, reduces costs, and improves the quality of patient care. By incorporating lean principles such as waste reduction and continuous improvement, healthcare organizations can optimize their supply chain operations. The case study of Caldwell UNC Healthcare demonstrates the significant achievements that can be realized through effective LSCM implementation, including notable cost savings and operational improvements. Technological advancements, such as artificial intelligence and big data analytics, further optimize demand forecasting, resource allocation, and inventory management. These technologies help healthcare providers reduce waste, mitigate supply shortages, and enhance overall supply chain performance. In addition, collaborative partnerships and accurate demand forecasting are critical for ensuring efficient resource allocation and streamlined operations. Despite its immense potential, the implementation of LSCM in healthcare presents several challenges. Barriers to successful adoption include inadequate digital infrastructure, regulatory restrictions, cultural resistance, and financial limitations. Overcoming these obstacles requires a robust digital infrastructure, effective regulatory navigation, a culture of continuous improvement, and sound financial management. Looking forward, LSCM holds great promise for transforming healthcare supply chains. Lean principles can be extended to outpatient services, and comprehensive quality metrics can be developed to further improve patient care and overall healthcare efficiency. Strategic partnerships with stakeholders—including insurance providers, pharmaceutical companies, and equipment suppliers—can enhance resource utilization and patient care delivery. The future of healthcare LSCM depends on continuous innovation, flexibility, and collaboration. By seizing these opportunities, healthcare organizations can maximize efficiency throughout the supply chain, ensuring high-quality and cost-effective patient care. This approach will contribute to the sustainability and resilience of healthcare delivery globally, addressing current challenges while preparing healthcare systems to meet future demands.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study.

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Author Contribution

Ginnel Quadras: Conceptualization and writing—original draft preparation and visualization; **Ali Talyshinskii**: Data curation and writing-original draft preparation; **Suhas Kowshik**: Visualization and Investigation.

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The Role of QR Code Technology in Revolutionizing Banking

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Abstract

The financial services industry has undergone a significant digital revolution, with QR code technology playing a crucial role in the development of the banking sector. Evolving from basic barcodes, QR codes have become essential tools for identity verification, secure online transactions, and financial account management. They represent a shift from conventional banking practices, offering enhanced security and user convenience. In banking, QR codes are used for account management, payments, and robust security protocols. The widespread adoption of QR codes has transformed how customers interact with banks and has led to stronger security measures for online banking. This article examines the growing use of QR codes in banking, highlighting the convenience, security, and improved customer experience these codes offer. The increasing importance of QR technology in banking is further demonstrated by emerging trends such as Data Matrix QR Codes, Blockchain-Enabled QR Codes, Secure Timestamping, Encryption, and Dynamic QR Codes.

Keywords: QR Code Technology; Digital Banking Security; Customer Experience In Banking; Blockchain-Enabled QR Codes; Dynamic QR Codes

1 Introduction

A Quick Response (QR) code consists of a series of black and white squares that can be read by machines, typically used to store websites or other types of data that can be scanned by a smartphone camera. It is a two-dimensional barcode, capable of capturing and retrieving data instantly using the camera on a smartphone [1]. QR codes are not a recent development—they were first invented in 1994 by the Japanese company Denso Wave, a subsidiary of Toyota [2]. In the rapidly evolving landscape of digital transformation, the banking industry has been at the forefront of implementing advanced technologies to enhance customer experiences and streamline operations. One significant advancement in banking operations is the widespread use of QR codes, along with their multi-level equivalents, as effective substitutes for traditional paper-based documents. This article explores the potential of QR codes as a revolutionary technology in the banking industry, focusing on their role in transforming money transfers and document management. Through a comprehensive review of the literature, we examine the current state of QR code adoption in banking, its advantages over traditional paper-based methods, and its limitations. We also consider emerging developments and future directions, envisioning a financial ecosystem where QR codes are integral to improving user experiences and expediting processes. A QR code is a two-dimensional barcode made up of a grid of black squares on a white background that can store large amounts of data. Common applications of QR codes include storing text, contact information, URLs, and other types of data. With the appropriate QR code scanning software and a mobile device equipped with a camera, these codes can be easily scanned. The software decodes the information embedded in the code and performs the necessary actions, such as opening a webpage, dialing a phone number, or sending a text message. QR codes are widely used in applications such as marketing, payments, ticketing, and authentication. Figure 1 below illustrates the basic structure of a QR code after it has been scanned.

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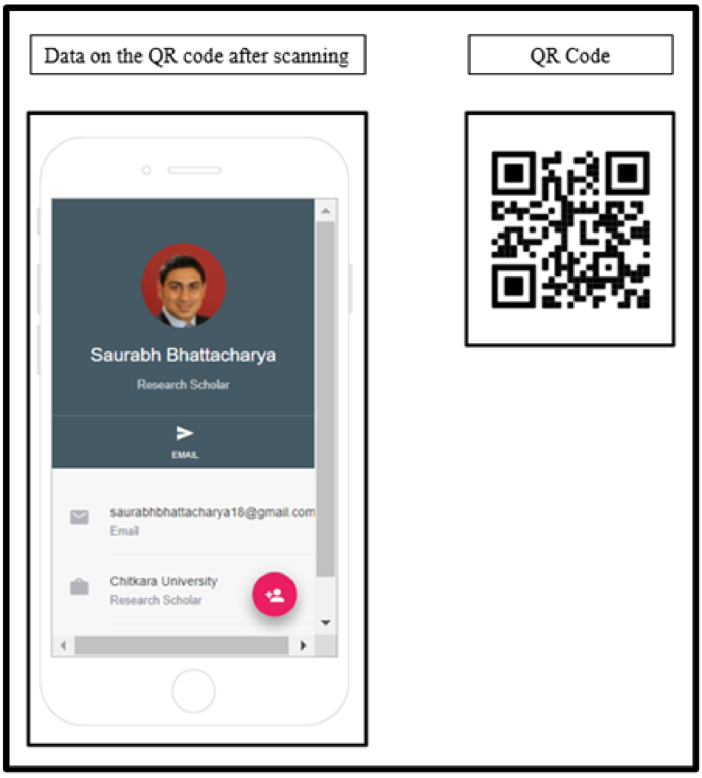

Figure 1: Basic QR code

The prevalence of QR codes in modern society reflects their convenience and efficiency in transmitting information. Within the banking sector, QR codes have revolutionized several processes by replacing traditional paper documents. This introduction examines the additional functionality offered by multi-level QR codes, which further enhance efficiency and security in banking operations. The introduction of QR codes has significantly improved reliability and customer satisfaction within banking. Traditional paper documents, such as account statements, invoices, and payment receipts, are increasingly being replaced by QR codes, which can be easily scanned using smartphones or other devices. This transition accelerates transaction times and reduces the environmental impact of paper usage, creating a more agile and responsive financial ecosystem [3]. QR codes are machine-readable, storing data both vertically and horizontally. They are also resilient—able to recover from errors if portions of the code are damaged—and can store up to 7,089 numeric characters, 4,296 alphanumeric characters, 2,953 bytes of binary data, or 1,817 Japanese Kanji/Kana characters, which is significantly more than a standard one-dimensional barcode [4]. The architecture of a QR code is layered, each layer contributing specific functionalities to ensure effective data encoding, structure, and decoding. Table 1 outlines the key layers involved in QR code architecture.

Table 1: QR Code Architecture Layers and Descriptions

Architecture Layer	**Description**
Data Layer	This layer includes the actual encoded data, such as alphanumeric characters, binary data, or byte arrays. It carries the information to be transmitted or stored.
Encoding Layer	The encoding layer involves the process of converting the data into a QR code matrix using specific algorithms, error correction codes, and patterns.
Structural Layer	The structural layer defines the format and structure of the QR code, including the positioning patterns, alignment patterns, timing patterns, and the overall grid layout.
Presentation Layer	This layer encompasses the visual representation of the QR code, including alignment markers, quiet zone, and potentially additional design elements, ensuring visual recognition.
Decoding Layer	The decoding layer involves the process of extracting and interpreting the encoded data from a scanned code using various algorithms and error correction techniques.

While manually decoding QR codes is not feasible for humans, scanning technology can easily interpret them. Many free QR code scanner apps are available for download, and most smartphones now come equipped with built-in scanning software. Once the QR code is decoded, the software takes appropriate actions based on the information embedded in the code. Depending on the data stored, the code can initiate actions such as calling a phone number, sending an SMS, displaying a webpage, or launching a specific app. The next innovation in this paradigm is the multi-level QR code, which allows the storage of more complex data, such as user-specific information, encryption keys, and transaction details. This multi-layered approach enhances security by enabling the encryption and compartmentalization of sensitive data within the QR code, reducing the risk of unauthorized access. Multi-level QR codes also facilitate a more streamlined and personalized banking experience. By integrating various features into a single QR code, users can access comprehensive information and complete multiple transactions with a single scan. This highlights the banking industry's commitment to offering a cutting-edge, customer-focused experience, while simplifying interactions for users.

The Mobile Technology Acceptance Model (MTAM) was specifically developed to adapt to mobile environments in information technology research. It comprises two key factors: Mobile Usefulness (MU) and Mobile Ease of Use (MEOU) [5]. In essence, the adoption of QR codes and multi-level QR codes in banking represents a significant shift away from paper-based processes towards a digitally advanced future. This transition supports environmental sustainability goals while enhancing operational efficiency. As banks continue to leverage QR codes, the industry is poised for further innovation, paving the way for a more interconnected and technologically sophisticated banking environment. Initially developed for tracking parts in the automotive industry, QR codes have since evolved into versatile tools with applications across various sectors. In banking, they have emerged as a transformative technology, streamlining information sharing and transaction processing. QR codes and their multi-level variants have become indispensable in the digital age, transforming banking operations by introducing paperless efficiency. This article examines the ways in which QR codes have reshaped the banking industry, highlighting their ability to accelerate processes, improve account management, and enable secure document storage. The advanced data segmentation and error-correcting capabilities of multi-level QR codes further enhance efficiency. By significantly reducing paper usage, the adoption of QR codes not only simplifies banking processes but also contributes to environmental sustainability. As the banking sector increasingly adopts QR codes, the technology has far surpassed traditional methods, ushering in a new era of unmatched efficiency and digitalization. This article explores how QR codes can be leveraged to drive the banking industry toward a paperless future, with a particular focus on the potential of multi-level QR codes [6].

2 Motivation

The growing significance of QR codes in transforming the conventional banking sector is the driving force behind the decision to investigate the different applications of QR codes in the banking sector. QR codes have become a major force behind the ongoing digital revolution of financial services, offering a secure and adaptable way to handle transactions, identification checks, and account management. Understanding the implications of QR codes in the banking sector is crucial to appreciating their influence on account management, payment processes, and security protocols. Furthermore, examining the significance of QR codes within the broader context of the banking ecosystem can provide valuable insights into potential advancements in customer experience, security, and efficiency. Thus, this study aims to investigate the various functions of QR codes in banking and elucidate their importance in shaping the future of financial services.

Table 2: Research Objectives and their Motivation

Research Objective	Motivation
To investigate the different use cases of QR codes in the banking sector	Understanding the various applications of QR codes in banking is essential for comprehensively evaluating their impact and potential benefits within the industry.
To analyze the current trends and challenges related to the use of QR codes in the banking sector	Identifying current trends and challenges provides insights into the evolving landscape of QR code usage and potential obstacles that may affect its widespread adoption.
To examine the impact of QR code integration on transaction security and customer data protection within the banking sector	Understanding the effects of QR code integration on security and data protection is crucial for evaluating its overall suitability and impact on banking operations and clients.

3 Research Questions

RQ 1: What are the different ways QR codes are being used in the banking sector?
RQ 2: What are the current trends and challenges of using QR codes in the banking sector?
RQ 3: How does the integration of QR codes in banking impact transaction security and customer data protection?

The given objectives align with the investigation of several aspects of QR code use in banking, including its application, current trends, challenges, and effects on transaction security and customer privacy. These questions provide a comprehensive framework for exploring the multifaceted role of QR codes in modern banking operations.

4 Related Work

The advent of mobile payment technologies, particularly Quick Response (QR) code-based systems, has resulted in notable disruptions across several business domains, with the retail industry being particularly affected. Despite this, significant obstacles remain in the widespread acceptance of mobile payment methods. Research has thus focused on important factors influencing the adoption of mobile payment technology based on QR codes in the retail industry. This research extends the Mobile Technology Acceptance Model (MTAM) to provide theoretical and practical insights for stakeholders in the retail business [5]. Two-dimensional barcodes are used in the QR-TAN authentication method to improve the security of electronic transactions. Unlike previous methods, QR-TANs enable users to validate transaction content on a trusted device, even if their computer has been compromised. When combined with smart cards, QR-TANs also facilitate secure offline transactions, offering critical protection against unauthorized transaction manipulation [7]. Dynamic capabilities have also been shown to significantly impact how well small and medium enterprises (SMEs) perform when using QR code payments and mobile money in developing nations. It is recommended that SMEs adopt digital financial services to improve performance and agility, particularly in volatile business environments such as the COVID-19 pandemic [8]. Mobile payments have transformed industries, especially retail, though government efforts have not yet fully increased the adoption rate in countries like Malaysia [5]. Systems incorporating security features, such as secret encryption algorithms and self-destruct mechanisms for security keys, offer additional protection against various attacks. The system also uses multiple key containers and physical security measures for enhanced safety [9]. QR codes are widely used in anti-counterfeiting and product traceability. However, since the source of QR codes is publicly available, the data they contain is not inherently secure. To mitigate this, encryption techniques like RSA and AES are recommended, though dynamic QR codes may be required to comply with national regulations and prevent duplication [10]. Researchers have explored using one-time passwords (OTPs) and QR codes as two-factor authentication (2FA) methods for website logins, emphasizing the need for 2FA in bolstering online security [11]. Honeywords and 2FA, when combined with mobile phones and QR codes, also improve password security [12]. For QR code payment security, visual secret sharing (VSS) is used in combination with QR codes to enhance anti-counterfeit safeguards. By stacking two QR code shares with merchant information, this technique confirms the legitimacy of QR code payments [13]. To combat product counterfeiting in e-commerce, blockchain technology and destructible QR codes can be employed, increasing transparency and authenticity [14]. Biometric authentication combined with QR code scanning is also used in online banking, reducing infrastructure costs and enhancing transaction security [9]. Research has shown that fingerprint-based identification with QR codes can streamline the check-in process for travelers by verifying their identity without requiring physical documentation [15]. Mobile banking security is improved with a hybrid solution that incorporates QR codes, OTPs, and digital watermarking [16]. QR codes are increasingly used in secure, visually appealing forms for digital payment and information sharing [17, 18]. To tackle counterfeit goods, Near Field Communication (NFC) technology has been proposed for consumer-level product authentication. By utilizing public key cryptography (PKC) and a public key infrastructure (PKI), this approach offers dual-layer authentication without relying on centralized databases [19, 20]. A systematic review of NFC technology highlights its applications in sectors like healthcare and public transportation [21, 22]. Finally, studies suggest that perceived risk, service quality, and transaction speed significantly affect the QR code mobile payment experience [23]. Insights into consumer behavior regarding mobile QR-code payments in China have shown that perceived security and utility are key factors driving user satisfaction and value perception [24]. Further analysis of the literature has identified key factors, such as personal innovativeness and social influence, that affect the adoption of QR code payment systems [25–28].

5 Research Methods

This study employed the Systematic Literature Review (SLR) methodology [29] to systematically investigate the role and use of QR codes in the banking sector. The SLR process consists of three main stages: planning, execution, and reporting. These stages are depicted in Table 3, which outlines the sub-stages and their descriptions. A total of thirty primary articles were included in this review, as illustrated in Figure 2. The steps involved in each stage of the process are described below. The search for relevant studies was conducted using a variety of academic databases, including Springer, Wiley, ScienceDirect, Google Scholar, and IEEE Xplore. The number of studies retrieved from each database is shown in Figure 2. After applying the inclusion and exclusion criteria, the final 30 studies were selected for detailed analysis.

Table 3: Stages and Sub-Stages of the SLR Process

Stage	Sub-Stage	Description
Planning	Formulate Research Questions	Clearly define the research questions and objectives for the review process.
Planning	Develop Search Strategy	Identify relevant databases, search engines, and repositories to systematically search for existing literature.
Planning	Preparation of Protocol	Outline the review process, inclusion/exclusion criteria, and data extraction methods.
Execution	Search and Screening	Implement the search strategy to systematically identify and retrieve relevant articles and documents.
Execution	Data Extraction	Extract relevant information from the selected studies using a standardized template for consistency.
Execution	Quality Assessment	Evaluate the quality and credibility of the selected studies using established tools or frameworks.
Reporting	Data Synthesis	Analyze and synthesize the findings from the selected studies, identifying common themes and gaps in the literature.
Reporting	Report Writing	Document the review findings in a comprehensive report, presenting the methodology, search results, and conclusions.
Reporting	Peer Review and Feedback	Seek feedback from peers, subject matter experts, or stakeholders to validate the review process and findings.
Reporting	Publication and Dissemination	Consider publishing the review in a reputable journal, presenting it at conferences, or disseminating the findings to relevant communities.

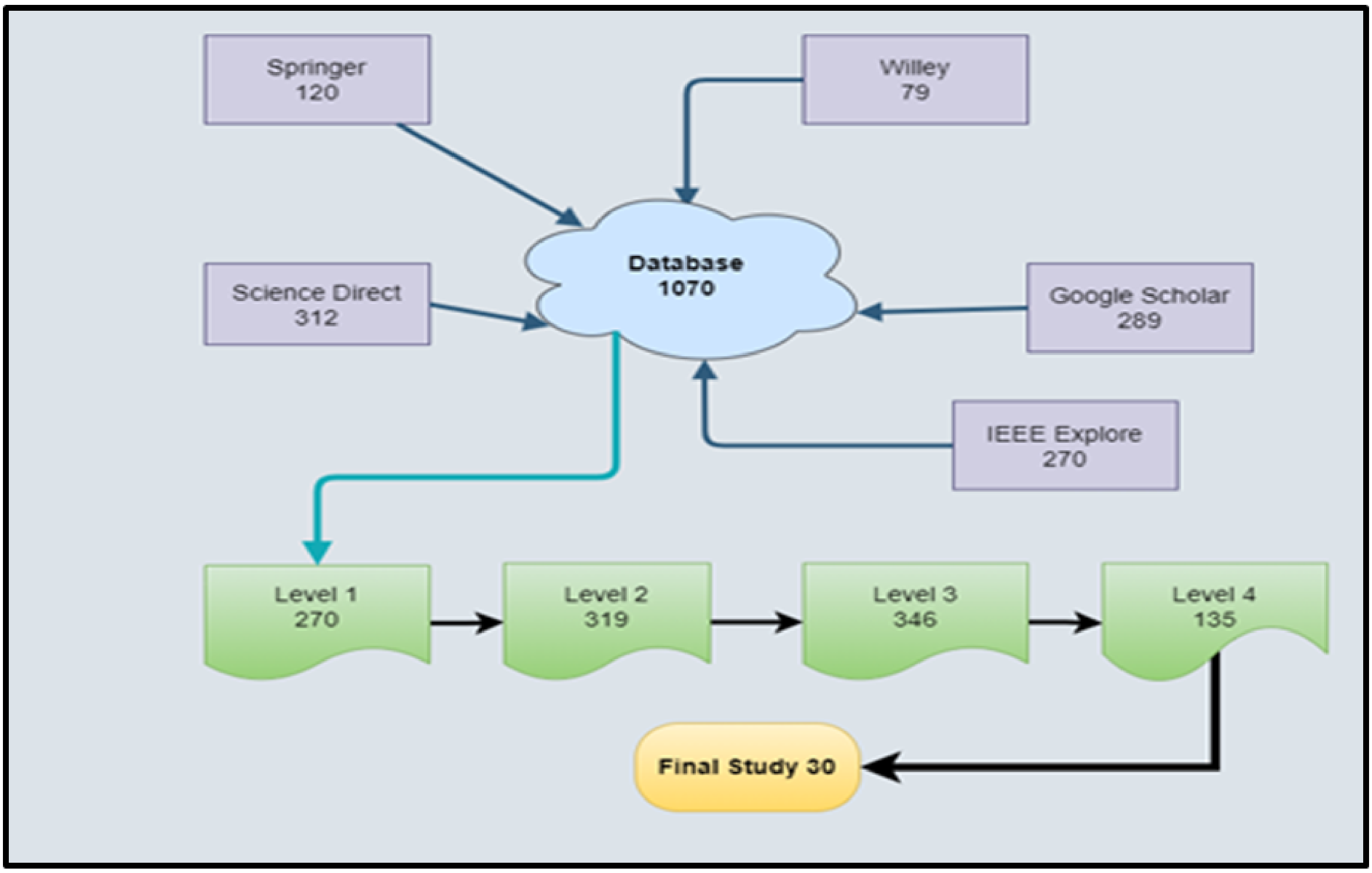

Figure 2: Search Database and Final Study Count

Table 4 provides the list of databases used in the search process along with their respective URLs. Based on the study's objectives, the following keywords were used to perform the search: *("QR Code" OR "Dynamic QR Code" OR "Static QR Code" OR "Biometric Authentication" OR "Two-Factor Authentication.")*

Table 4: Search Databases

Source	Website
Scopus	https://www.scopus.com
IEEE Xplore	https://ieeexplore.ieee.org
Google Scholar	https://scholar.google.com
Springer	https://www.springer.com
ScienceDirect	https://www.sciencedirect.com

6 Discussion on Selected Articles

RQ 1: What are the different ways QR codes are being used in the banking sector?

The research questions are thoroughly addressed in this section to ensure that the goals of the study are clear. The introduction of QR codes in banking has resulted in substantial improvements in transaction security and customer data protection. QR codes streamline the authentication processes for a range of financial services, providing customers with a quick and secure way to initiate transactions. By utilizing QR codes, financial transactions expose less sensitive data, increasing transaction security. Furthermore, employing QR codes for authentication reduces risks associated with traditional methods, such as phishing and unauthorized access. QR codes have enabled contactless payments and peer-to-peer money transfers, eliminating the need for face-to-face interactions and reducing the potential exposure of sensitive data. Contactless payment technologies lower the risk of fraud by preventing the interception of payment information. The encrypted nature of QR codes enhances customer data security, lowering the risks of unauthorized access to financial and personal information. The various application of QR code authentication found in the banking sector are:

- **Mobile Banking Apps**: Financial institutions and banks use QR code authentication to ensure safe login and transaction authorization within their mobile apps.
- **Two-Factor Authentication (2FA)**: QR codes link and create secure user accounts, providing an additional layer of security to online services.
- **Secure Messaging Channels**: Messaging services use QR codes for safe device authentication and linkage, ensuring encrypted communication.
- **Access Control Systems**: QR codes manage and verify entry to restricted areas or buildings.
- **Secure Document Sharing**: QR codes validate documents and allow sensitive information to be transmitted efficiently and securely.

Table 5: Use Case with Pros and Cons of Various QR Code Types

Aspect	Static QR	Dynamic QR	2FA QR	Biometric QR	Blockchain-enabled QR
Data Storage	Store fixed data only	Store and display data that can be updated	Store data for two-factor authentication	Store biometric data for user authentication	Store data in a decentralized and secure manner
Use Case in Banking	Account information, payment requests	Real-time updates on account balance, promotions	Two-step verification, login authentication	User identification, access control, transaction authorization	Secure transactions, asset tracking, authentication, validation
Pros	Simple to generate and use, can be static for repeated use	Real-time updates, versatile applications, marketing tool	Added layer of security, mitigates unauthorized access	Enhanced security, convenience for users	Immutable data records, increased security, decentralized verification
Cons	Limited functionality, not suitable for real-time data	Complex generation and management, potential data misuse	Dependency on second factor, inconvenience for users	Reliability and accuracy of biometric data, potential privacy concerns	Integration challenges, specialized knowledge and support may be required

The latest QR code techniques in Banking in the present day are:

- **Dynamic QR Codes**: These QR codes can store information that changes over time, such as transaction amounts and details. This allows for flexible transactions while enhancing security.
- **QR Authentication**: By utilizing QR codes for multifactor authentication, users can securely access accounts and approve transactions.
- **QR-based Payment Applications**: Many banks are developing apps that enable customers to transfer money, pay bills, and make contactless purchases using QR codes.
- **Secure QR Code Scanning**: Organizations have implemented safe scanning systems to ensure QR codes are authentic and unmodified before processing transactions.

RQ 2: What are the current trends and challenges of using QR codes in the banking sector?

QR codes can serve as a vector for phishing attacks, potentially leading to fraudulent transactions and unauthorized access to personal financial information. Concerns have been raised regarding customer data privacy when using QR codes for transactions and authentication, especially if the data is intercepted or handled improperly. As the use of QR codes in banking grows, standardized methods and interoperable technologies are essential to ensure simple and secure transactions across multiple platforms and institutions. To mitigate potential security and privacy issues, it is crucial to inform customers about the risks and best practices associated with using QR codes in banking. The rise of mobile banking apps has completely transformed how payments are made, making it easier for customers to manage financial activities while improving the standard of service in the financial industry. The COVID-19 pandemic accelerated the widespread adoption of mobile banking applications, including the use of QR codes, as they provide a flexible and dynamic way to simplify many operations [28]. Customers can now perform payments, make purchases, and transfer money without physical interaction thanks to QR codes. These transactions are more efficient, eliminating the need for paper cards or manual data entry. Studies show that banks are increasingly using QR codes for a variety of purposes, such as client interactions, account management, and payment facilitation [30].

Table 6: Trends in QR Code Usage in the Banking Sector

Trend	Use Case for Banking	Pros	Cons	Challenges
Dynamic QR	Real-time payments, account management, secure data updates	Enhanced security, ability to change and update data	Requires network availability for real-time updates	Data synchronization, potential for abuse or misuse
Secure Encoding Standards	Secure transactions, data integrity assurance	Protection against tampering, unauthorized access, and modification	Implementation complexity, potential performance impact	Standardization, interoperability, education on secure coding and practices
Mobile Security Features	Secure customer authentication, transaction verification	Biometric and device-specific authentication, enhanced user security	Potential for user inconvenience, device compatibility concerns	Data privacy, user acceptance, secure storage of biometric data
Anti-Counterfeiting Measures	Secure payments, product authentication	Reduced counterfeiting, enhanced trust and authenticity	Additional production costs, potential user confusion	Standardization, scalability, validation methods
Secure QR Scanning Apps	Secure payment processing, user protection	Protection against malware, phishing, and other security threats	Dependence on app security, potential for false sense of security	User adoption, app standardization, threat landscape changes
Blockchain-enabled Verification	Secure and tamper-proof transactions, data integrity	Decentralized verification, tamper-resistance, transparency	Blockchain complexity, resource-intensive validation process	Integration with existing infrastructure, regulatory acceptance

Driving Forces Behind QR Code Adoption in Banking

QR codes have become a powerful tool in banking to improve client experiences and streamline operations. They are used for a range of purposes, from document authentication and transmission to payment systems and account management. QR codes allow consumers to quickly access information and complete transactions using their mobile phones. This technology has become a critical component of wireless payment solutions, enabling users to make purchases without needing cash or physical cards. QR codes also play a significant role in facilitating secure and fast money transfers between banks, offering a more practical alternative to traditional paper records [31]. The adoption of QR codes in banking has reached a pivotal stage, revolutionizing financial transactions and enhancing customer experiences. However, it is crucial to address security, standardization, and interoperability concerns to ensure sustainable expansion.

RQ 3: How does the integration of QR codes in banking impact transaction security and customer data protection?

The use of QR codes in banking can affect client data privacy and transaction security in both positive and negative ways. Security in the financial sector is critical. To ensure the secure storage of private financial information, QR codes have been rigorously evaluated. Numerous researchers have examined the security features of QR codes, identifying weaknesses and offering solutions to safeguard the integrity of financial transactions. QR codes provide various positive impacts in banking.

They enable contactless transactions, reducing the risk of in-person theft and unauthorized access to sensitive customer data. QR codes can also contain encrypted data, providing a secure method of transferring transaction data from the customer's device to the bank's servers. Moreover, some QR code payment systems support two-factor authentication (2FA), which adds an extra layer of security for verifying transactions and protecting client information. A novel approach to 2FA suggests replacing SMS-based authentication, which is considered less secure, with QR codes containing steganography. This method hides mobile transaction authentication numbers (mTANs) within the QR code, making the data accessible only through a specific scanner with the shared key [32, 11]. However, QR codes also come with potential negative impacts. Malicious actors can create fake QR codes to trick customers into scanning them, leading to data breaches or financial loss through phishing and spoofing. The security of the customer's device is also crucial when using QR codes because compromised devices could expose transaction data to unauthorized parties. Additionally, if proper security precautions and encryption are not employed, data encoded in QR codes could be intercepted during transmission. To mitigate these negative impacts and enhance transaction security and customer data protection, banks must implement robust encryption mechanisms, authentication protocols, and customer education programs. These measures help ensure that QR codes can be safely integrated into banking operations, protecting both customer data and transaction integrity. Several studies have highlighted the critical role of QR codes in transforming financial payment systems. Researchers demonstrate that QR codes can be used in mobile payments, making transactions safe and easy to execute [33]. Customers benefit from QR codes through greater convenience, as they can easily complete various banking transactions using mobile devices, such as paying bills and checking account balances, without needing cumbersome authentication methods or physical cards. Banks increasingly adopt QR codes to enhance security during login and transaction authorization processes, with additional layers of protection offered by technologies like tokenization, encryption, and dynamic QR codes. These solutions help reduce the risk of fraud and unauthorized access while offering cost-effective modernization for banking institutions, with minimal infrastructure required to implement QR code-based services.

QR codes are also improving the overall management of customer accounts. With a quick scan, customers can securely access account balances, view transaction histories, and perform other account management tasks, streamlining the user experience. For instance, QRAM (Quick Response Code-based Authentication Methods) enhances security in IoT applications and real-time systems by speeding up verification times for QR codes, demonstrating higher resilience against unauthorized access attempts. Additionally, watermarked QR codes have been integrated into mobile banking apps, providing high security against unauthorized access and eavesdropping during online transactions [34]. The transition to QR code-based digital alternatives in banking has significant implications. First, it promotes environmental sustainability by reducing paper use and minimizing resource consumption. Moreover, QR codes improve operational efficiency by enabling faster, more accurate data processing, saving time and resources previously used for manual document handling. This shift to digital methods also aligns with the larger trend of digitization within the banking industry. By adopting these technologies, banks can remain competitive, satisfy the demands of tech-savvy customers, and stay at the forefront of innovation. The ease of use provided by QR codes improves the overall customer experience, enhancing satisfaction and loyalty.

7 Conclusion

The use of QR codes in banking has provided customers with a safe and efficient way to access banking services through mobile apps while ensuring data protection. Given the widespread adoption of smartphones, users can now securely access sensitive data and log into their accounts using QR codes, which have proven to be a useful and user-friendly technology. Compared to traditional username-and-password-based security methods, QR codes offer enhanced customer data protection. In summary, the adoption of QR codes in banking has delivered significant benefits in both transaction security and customer data protection. The introduction of QR codes has notably reduced the exposure of sensitive data, accelerated identification processes, enabled contactless payments, and improved accessibility to financial services via mobile applications. Consequently, QR codes have become a valuable tool in the banking sector for strengthening transaction security and safeguarding customer data. However, further research and ongoing evaluation are necessary to ensure the long-term sustainability of QR code integration in banking and to adapt to evolving security challenges. This study emphasizes the importance of QR code technology in enhancing transaction security and customer data protection, ultimately offering clients a safer and more secure banking experience.

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

Saurabh Bhattacharya: Conceptualization, Methodology, Investigation, Writing - original draft, review, and editing. **Babita Singla**: Investigation, Visualization, Resources.

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The Applications of Tissue Engineering: A Beginner's Perspective on Burn Treatment and Cancer Drug Delivery

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Abstract

This short communication article provides a beginner's perspective on tissue engineering, elucidating its applications in burn skin treatment and drug delivery systems for cancer therapy. The first part discusses the challenges and current issues related to burn injuries, exploring engineered techniques for their treatment. It emphasizes the need for scaffolds in skin tissue regeneration, detailing the materials and methods used. The second part focuses on drug delivery mechanisms in tissue engineering, specifically in cancer treatments. It explains the carrier and release mechanisms of drugs targeting cancer cells and reflects on personal learning experiences from the course. The article synthesizes personal comments and learning reflections in the conclusion, making it accessible for those who wish to grasp the concept of tissue engineering at a glance.

Keywords: Burn Injuries; Drug Delivery; Artificial Tissues; Scaffolds; Tissues Engineering

Introduction

Tissue engineering is a multidisciplinary field that redefines treatment methods for biological complications through technological advancements. In recent years, tissue engineering has undergone significant changes due to discoveries in additive manufacturing, biomaterials, and cellular reprogramming. Burns are physical injuries caused by exposure to heat, friction, chemicals, electrical discharge, or radiation. According to the Global Burden of Disease (GBD), approximately 8.3 million cases of burns were reported globally in 2019 [1]. Burn injuries are classified into four degrees based on the depth of the injury, as illustrated in Figure 1. Medical or surgical interventions are determined accordingly. The healing process is complex and time-consuming, often requiring expensive interventions such as plastic surgery. Conventional burn treatments include wound care, skin grafting, and surgical procedures. Scarring is inevitable in the healing process, leading to psychological challenges for burn survivors in societies where aesthetic concerns are prominent. Burn injuries result in lifelong physical and psychological scarring, causing pain, affecting mental health, quality of life, the ability to return to work, and increasing mortality [2]. Treating burn injuries presents numerous challenges, including skin infection, prolonged healing time, intense pain, functional impairments, the need for intensive care facilities, fluid and electrolyte imbalances, poor grafting, graft rejections, and increased treatment costs. Skin grafts often require donor tissue from the same person, a biologically identical person, or animals, leading to complications such as infection, cell rejection, and donor site morbidity. Tissue engineering offers solutions that address many challenges posed by conventional burn injury treatments. Its applications in skin treatment can be categorized into four methods: tissue scaffolds, healing promotive factors, stem cells, and gene therapy [3].

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Figure 1: Classification of burn wounds by depth. Clinical examples of burn degrees: (a) First-degree burn, (b) Second-degree burn, (c) Third-degree burn, (d) Fourth-degree burn.

Tissue Engineering in Skin Treatment

Skin, being the largest organ of the body, serves as an ideal candidate for tissue engineering applications aimed at regeneration and repair. The three major components in tissue engineering are:

1. **Cells**: Functional cells used for regeneration.
2. **Scaffolds**: Structures for cell-matrix adhesion.
3. **Signals**: Factors that direct growth and cell differentiation, originating from immune and damaged cells.

Advancements in stem cell technology have enabled the use of proliferated stem cells to promote cell differentiation near the extracellular matrix, facilitating the repair of burned skin through cell transplantation. Precise localization of stem cells at the wound site is crucial for effective regeneration. However, challenges such as host immune system rejection and chemical composition can lead to treatment failure. Scaffolds act as replicas of the extracellular matrix, functionally mimicking tissues at the defect site. They provide infrastructure for cell growth and differentiation, leading to proper tissue regeneration. Figure 2 compares wound closure with and without scaffold intervention.

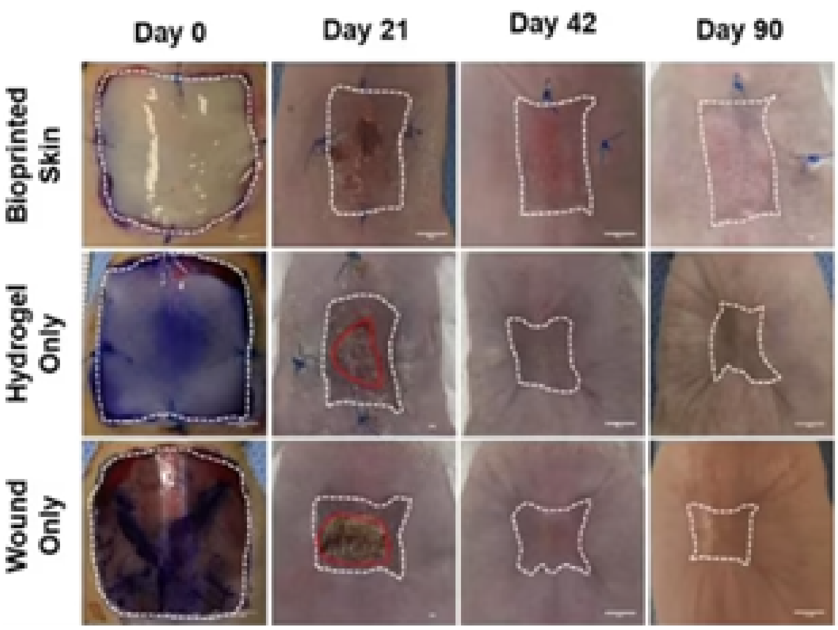

Figure 2: Comparison of wound closure: (a) Traditional healing process without scaffold intervention, (b) Enhanced healing with scaffold-based tissue engineering approaches.

Materials used as scaffolds include natural polymers such as collagen, chitosan, gelatin, elastin, fibrin, keratin, and fibropin, as well as synthetic polymers like Poly(lactic-co-glycolic acid) (PLGA), Polyethylene Glycol (PEG), Polycaprolactone (PCL), Polyethylene Terephthalate (PET), Polyvinyl Alcohol (PVA), Polyglycolic Acid (PGA), Poly(ϵ-caprolactone-co-lactide) (PCLA), and Polyacrylonitrile (PAN). Growth factors and peptide-loaded hydrogels, including Epidermal Growth Factor (EGF), Fibroblast Growth Factor (FGF), Platelet-Derived Growth Factor (PDGF), Vascular Endothelial Growth Factor (VEGF), Insulin-like Growth Factor (IGF), Hepatocyte Growth Factor (HGF), Transforming Growth Factor-beta (TGF-β), and Keratinocyte Growth Factor (KGF), are also utilized [4, 5]. The selection of cells, scaffolds, and growth factors—or combinations thereof—is based on individual cases and the injury location. Scaffolds can be 3D porous, fibrous, or particulate structures that promote cell growth. Cells extracted from the body, such as keratinocytes, fibroblasts, melanocytes, adipocytes, induced pluripotent stem cells, and mesenchymal stem/stromal cells, serve as precursors for regeneration. The effectiveness of scaffolds is determined by their biocompatibility, cell attachment and proliferation in the extracellular matrix, replication of nearby tissue's mechanical properties, surface topology, extent of vascularization, and inflammatory responses.

Drug Delivery in Oncology

Cancer is characterized by uncontrolled cell growth and proliferation, with the potential to spread to nearby tissues through metastasis. The variable nature of cancer cell growth poses significant challenges for medical interventions, leading to considerable mortality each year. The majority of cancers occur in the lungs, followed by the liver, colorectal region, stomach, and breast [6]. Chemotherapy, a common cancer treatment, is associated with side effects such as weakness, fatigue, nausea, hair loss, and vomiting [7]. Recent advancements have introduced nanoparticle drug delivery as a promising approach in oncology. Nanoparticles, characterized by their small size and unique physicochemical properties, offer a tailored and targeted approach to drug delivery, enhancing the efficacy of anti-cancer drugs while minimizing systemic side effects. Various types of nanocarriers used in medical applications are illustrated in Figure 3. These include:

- **Inorganic Nanocarriers**: Single-walled carbon nanotubes, gold nanocarriers, magnetic nanocarriers, quantum dots, mesoporous silica nanocarriers.
- **Organic Nanocarriers**: Solid lipid nanocarriers, liposomes, dendrimers, polymeric nanocarriers.
- **Hybrid Nanocarriers**: Polymeric-lipid nanocarriers.

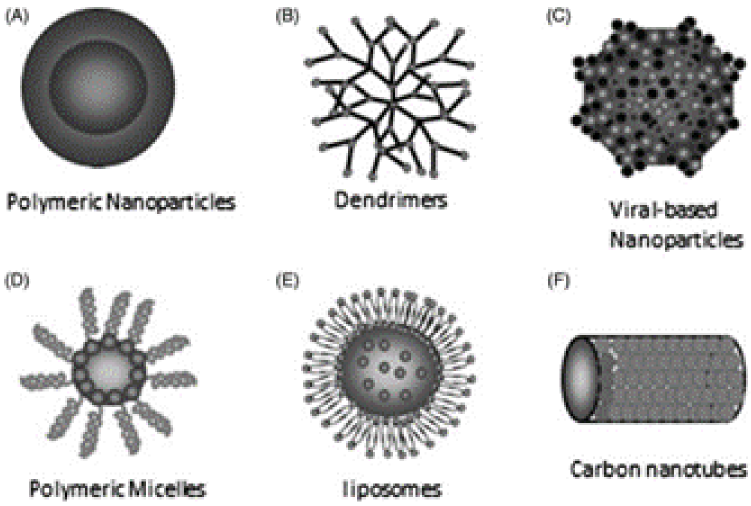

Figure 3: Types of nanocarriers used for drug delivery in cancer therapy.

These nanocarriers provide precise control over drug release, improved bioavailability, and the ability to selectively target cancer cells [8].

Drug Delivery Mechanism

Nanocarriers typically range from 1 to 100 nm and possess colloidal characteristics. They are compounds loaded with anti-cancer drugs and can be customized with functional groups for targeting specific environments—a process known as functionalization. Drug loading strategies include covalent bonding conjugation, encapsulation, and electrostatic interaction. Targeting mechanisms involve direct administration at the target site, directing magnetic nanocarriers using magnetic fields, active targeting, and passive targeting. The schematic of nanoparticle responses is depicted in Figure 4. Drug delivery using nanoparticles can be mathematically modeled using various kinetic models such as the diffusion model, Peppas model, first-order release kinetics, zero-order release kinetics, Weibull model, Hixson–Crowell model, Hopfenberg model, and sequential layer model [9].

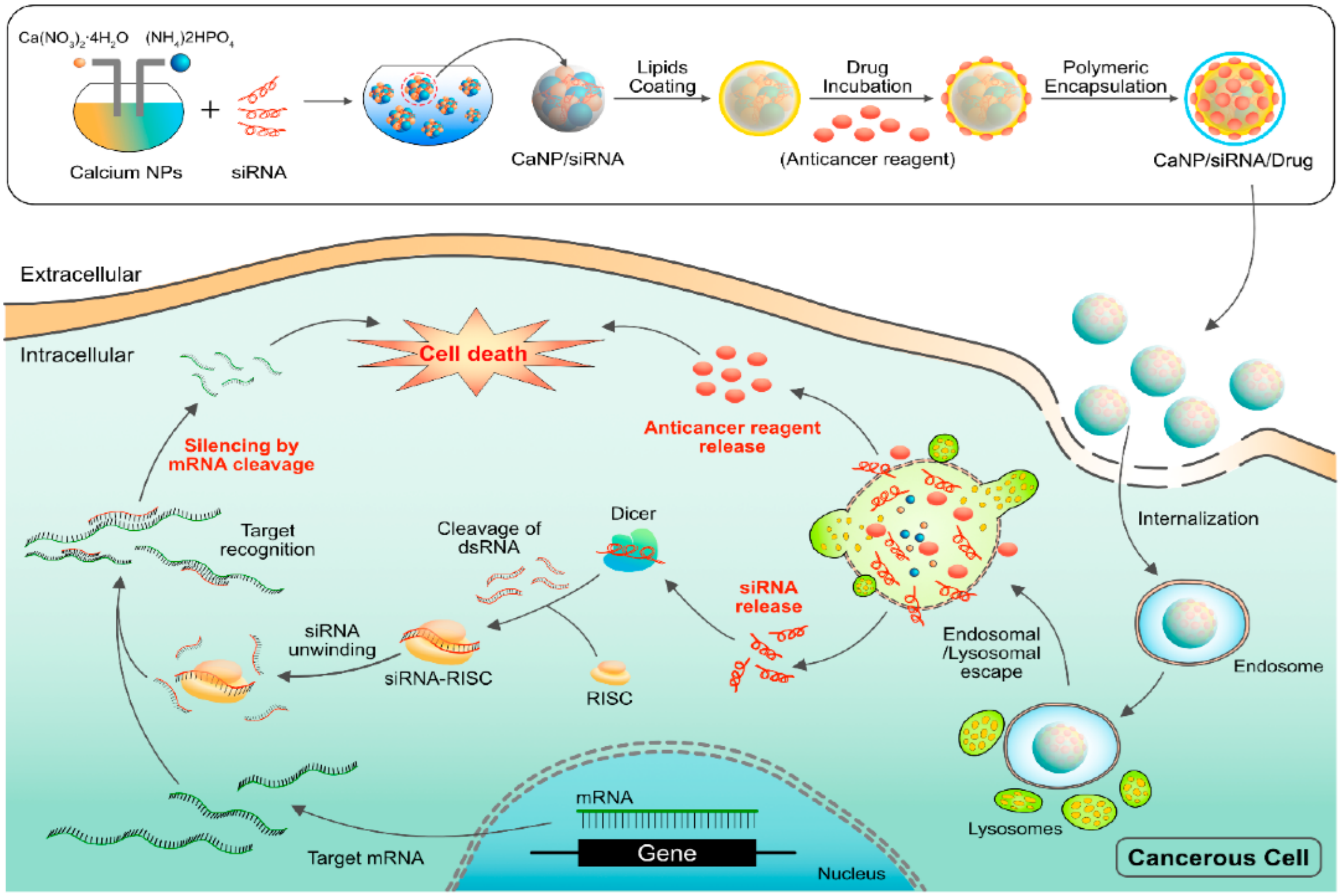

Figure 4: Schematic representation of nanoparticle responses in drug delivery systems, illustrating stimuli-responsive mechanisms for controlled drug release.

Once the nanoparticle enters cancer cells, it reaches the lysosomal compartments to release the drug. Rapid release of a drug into the interstitial space from the nanoparticles may cause premature release and systemic side effects, while slow release decreases drug efficacy and increases multidrug resistance. Therefore, the drug is designed to be released according to *in vivo* physiological conditions or external stimuli. Internal stimuli mechanisms include pH changes, redox reactions, reactive oxygen species (ROS), enzymes, hypoxia, inflammatory mediators, adenosine triphosphate (ATP), and ionic microenvironments. External stimuli include temperature, ultrasound (mechanical stress modulation), magnetic fields, electric fields, and light. The interaction efficiency of nanoparticles with biological or targeted tissues influences the overall treatment effectiveness. Biocompatibility of nanocarriers is of utmost concern. Materials that are biologically non-harmful or have low toxicity, along with surface modification, generally attract proteins onto the surface of the carrier, facilitating easier binding. The testing pipeline typically involves *in vitro* studies to assess cellular responses and drug release mechanisms, followed by *in vivo* studies in animal models to evaluate efficacy, toxicity, immunogenicity, and other factors.

Conclusion

This article provides an overview of tissue engineering applications in burn injury treatment and drug delivery systems for cancer therapy. It elucidates the basics of tissue engineering, scaffold systems, biocompatibility, and drug delivery mechanisms. By examining specific applications such as burn skin treatment and nanoparticle-mediated drug delivery to cancer tissues, the article highlights the innovative solutions that tissue engineering brings to modern medicine. The detailed analysis of materials and methods used in scaffold creation and drug delivery systems, including the use of natural and synthetic polymers, growth factors, and various types of nanocarriers, offers valuable insights into the current state and future directions of this rapidly evolving field. By translating complex scientific concepts into accessible language, this article serves as a useful resource for those seeking to understand the fundamental principles and applications of tissue engineering. Through continued research and technological advancements, the potential for improved treatments and better patient outcomes in both burn injuries and cancer therapy remains vast and promising. The integration of interdisciplinary approaches in tissue engineering holds the key to unlocking new therapeutic possibilities and enhancing the quality of life for patients worldwide.

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