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Editorial Comments Volume 4 Issue 3

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Volume 4, Issue 3 of the *Journal of Computers, Mechanical, and Management* showcases significant contributions spanning precision medicine, education, environmental sustainability, and decentralized IoT systems. Each article embodies the journal's core commitment to interdisciplinary innovation, system scalability, and real-world applicability. Sunil P. Chinte et al. [1] proposed a blockchain-based decentralized storage framework for scalable and secure IoT data management. Through simulations with Hyperledger Caliper and Ethereum Testnets, the study demonstrated a 30% reduction in data retrieval time, 25% storage efficiency gain, and 50% throughput increase, establishing a robust model for smart cities and industrial systems. Sumit R. Raut et al. [2] integrated molecular dynamics and density functional theory with experimental techniques for the synthesis of advanced nanomaterials in environmental remediation. The materials exhibited 95% heavy metal and 90% organic pollutant removal efficiencies, with adsorption capacities reaching 500 mg/g, reinforcing the efficacy of simulation-guided material design. Ram Kumar Solanki et al. [3] introduced a smart water management architecture using IoT, big data analytics, and blockchain. The 30-day simulation with 50 sensor nodes led to a 20% water quality improvement and a 7% reduction in consumption, contributing to sustainable urban and agricultural water governance. B. Arthi et al. [4] applied AI and ML techniques in precision medicine, focusing on adaptive diagnostics and personalized treatment pathways. The study's predictive model significantly outperformed traditional diagnostic methods, with particular efficacy in oncology and cardiology, supporting targeted and cost-effective healthcare solutions. M. Amarnath Reddy et al. [5] developed an AI-driven decision support system to forecast academic performance in higher education. By integrating machine learning with multidimensional student data, the model achieved over 90% accuracy and emphasized explainability and scalability in educational analytics. This issue emphasizes the convergence of computational intelligence, secure infrastructure, and sustainability, underscoring JCMM's role in driving technological excellence. The editorial board thanks the authors and reviewers for their valuable contributions.

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Artificial Intelligence and Machine Learning in Precision Medicine: Applications, Challenges, and Ethical Perspectives

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Abstract

Artificial intelligence (AI) and machine learning (ML) are transforming healthcare delivery by facilitating the development of precision medicine, which prioritizes personalized diagnostic and treatment strategies based on individual genetic, physiological, and lifestyle profiles. This study investigates the contributions of AI and ML in enhancing clinical decision-making, improving diagnostic accuracy, and supporting remote patient management. A mixed-methods framework was applied, combining quantitative analysis of clinical datasets with qualitative interviews and real-world case evaluations. Machine learning algorithms, including convolutional neural networks and ensemble models, were trained on public datasets to assess their impact on diabetes and cardiovascular care. Results showed significant improvements in glycemic control and reductions in hospital readmissions, indicating effective treatment personalization. Semi-structured interviews with patients and healthcare professionals revealed strong support for AI-enabled tools, highlighting perceived benefits such as increased efficiency, ease of use, and diagnostic clarity. Case studies of wearable health devices and telemedicine systems demonstrated enhanced care accessibility and a reduction in in-person clinical consultations. Ethical and operational challenges were identified as key concerns. Issues such as data privacy, algorithmic bias, lack of explainability, and the need for sustained human oversight were recurrent themes in stakeholder feedback. These challenges underscore the necessity of implementing transparent, accountable, and ethically grounded AI systems in clinical practice. The study underscores the dual necessity of technological capability and ethical rigor in deploying AI for precision medicine. Through a comprehensive analysis of clinical, experiential, and operational data, the research highlights both the promise and the complexity of integrating AI in modern healthcare environments.

Keywords: Artificial Intelligence; Machine Learning; Precision Medicine; Healthcare Ethics; Personalized Treatment

1. Introduction

Artificial intelligence (AI) and machine learning (ML) are significantly transforming healthcare delivery, particularly within the context of precision medicine. Precision medicine emphasizes individualized treatment protocols tailored to the distinct genetic, physiological, and environmental attributes of each patient. The integration of AI and ML facilitates the synthesis and interpretation of complex biomedical data, thereby enabling timely diagnoses, refined clinical decision-making, and improved therapeutic outcomes.

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Advanced algorithms such as convolutional neural networks (CNNs) and support vector machines (SVMs) are increasingly utilized in medical image analysis, demonstrating notable efficacy in the identification of pathological patterns associated with oncological and cardiovascular disorders [1]. In the domain of genomics, AI is instrumental in interpreting high-dimensional data to uncover relationships between genetic variations and therapeutic responses, particularly in oncology [1]. These computational tools enhance precision by aligning medical interventions with individual genomic profiles. Beyond traditional clinical environments, AI-augmented technologies such as wearable sensors and telemedicine infrastructures contribute to continuous patient surveillance and early intervention [2]. These innovations broaden the reach of medical services, promoting accessibility and reducing the dependency on physical healthcare infrastructure. However, the adoption of AI in healthcare introduces multifaceted ethical and operational challenges. Concerns regarding the integrity and confidentiality of patient data, algorithmic fairness, and the opacity of decision-making models persist [3, 4].

Moreover, the balance between automated systems and human clinical judgment remains a critical issue in ensuring responsible application. This study investigates the multifarious applications of AI and ML within precision medicine. It systematically examines their influence on diagnostic enhancement, ethical considerations pertaining to bias and privacy, the customization of treatment strategies based on individual health data, and the efficacy of AI-driven remote healthcare delivery systems. Through an integrated analysis of empirical outcomes, user perspectives, and case-based evaluations, the study aims to elucidate both the advantages and the limitations associated with the deployment of AI in contemporary medical practice.

2. Related Work

Extensive research has been conducted on the applications of artificial intelligence (AI) and machine learning (ML) across diverse healthcare domains, encompassing clinical utility, ethical implications, and system-level integration. In medical imaging, AI-driven frameworks such as convolutional neural networks (CNNs) have exhibited diagnostic accuracy comparable to or surpassing that of expert clinicians, particularly in the detection of tumors and other critical anomalies [1, 5]. These advancements have proved vital in specialties such as gastrointestinal diagnostics [6] and ophthalmology [7], where early detection markedly influences clinical outcomes. In genomic medicine, AI continues to facilitate the interpretation of complex omics data, enabling the personalization of therapeutic regimens for multifactorial diseases including cancer and renal pathologies [1, 8]. AI methodologies have similarly advanced pediatric diagnostics, particularly within oncology, by enhancing the speed and accuracy of clinical evaluations [9]. Moreover, in rare disease contexts, where traditional data may be sparse, AI algorithms excel at extracting meaningful patterns that assist in early and precise identification [10]. Beyond diagnostic support, AI technologies contribute to real-time health monitoring through integration with wearable sensors and telehealth platforms, thereby improving accessibility and continuity of care [2, 11]. These developments extend clinical oversight beyond conventional settings, allowing healthcare providers to intervene promptly based on continuously updated patient metrics. Despite these technological advancements, ethical considerations persist. Issues such as the transparency of algorithmic decision-making, potential biases embedded in training datasets, and concerns regarding the erosion of patient autonomy continue to provoke critical scrutiny [3, 12]. Empirical studies suggest that AI systems are more favorably received by clinicians when positioned as decision-support tools rather than autonomous entities [2, 13]. Nevertheless, automation bias and the opacity of some models raise concerns about over-reliance and misinterpretation [7, 5]. To mitigate these risks, scholars have proposed governance frameworks emphasizing ethical principles such as fairness, accountability, and algorithmic explainability [14]. However, regulatory oversight remains limited, and many AI applications have yet to undergo rigorous clinical validation or integration into standardized medical protocols [4, 13]. This study builds upon the existing literature by synthesizing clinical performance data, stakeholder perceptions, and real-world deployment evidence. Such a comprehensive approach aims to bridge existing gaps and offer a more cohesive understanding of AI and ML deployment within precision medicine.

3. Methods

This study employed a mixed-methods design to systematically investigate the applications of artificial intelligence (AI) and machine learning (ML) within the domain of precision medicine. The methodology was organized into three sequential phases, each targeting a distinct dimension of AI integration in healthcare: clinical performance evaluation, stakeholder insight collection, and contextual implementation assessment. In the first phase, quantitative analyses were conducted on clinical datasets involving patients diagnosed with diabetes and cardiovascular conditions. Machine learning models, including convolutional neural networks (CNNs) and ensemble techniques such as random forests and gradient boosting, were implemented to assess diagnostic precision and treatment customization capabilities. Publicly accessible datasets, namely MIMIC-III and The Cancer Genome Atlas (TCGA), served as primary data sources. The models were constructed and validated using established Python libraries such as `scikit-learn` and `TensorFlow`. Evaluation metrics—sensitivity, specificity, precision, recall, and overall error rate—were used to determine the effectiveness of AI-based predictions relative to conventional diagnostic methods. The second phase focused on qualitative inquiry. Semi-structured interviews were conducted with a purposive sample of 150 patients and 50 healthcare professionals, encompassing clinicians, software developers, and bioethics experts. Participants were selected to ensure representative coverage of roles involved in AI applications and oversight. Interview transcripts were processed using grounded theory methodology, coded with NVivo software. Key thematic domains included data privacy, algorithmic trust, decision transparency, perceived utility, and potential ethical dilemmas. The third phase adopted a case study framework to examine the deployment and practical utility of AI-driven technologies such as wearable health monitors and telemedicine platforms. Documentation reviews, platform usage logs, and targeted interviews with clinicians provided insights into operational performance, patient adherence, and system scalability. These real-world implementations were evaluated for their capacity to reduce in-person consultations while maintaining or enhancing care continuity and responsiveness.

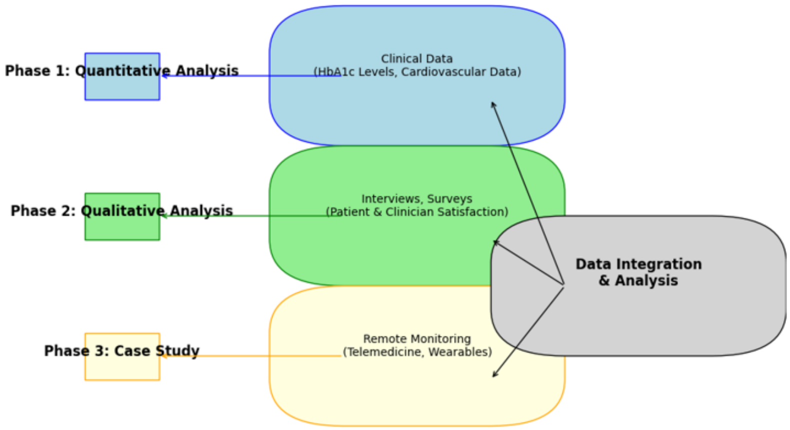

Figure 1: Overview of the study's three-phase methodology and data integration approach

4. Results

The empirical evaluation revealed measurable improvements in clinical outcomes when AI-informed strategies were employed. For patients managing diabetes, the application of AI-guided treatment protocols led to enhanced glycemic regulation across a 12-month observation period. A consistent downward trend in HbA1c levels indicated that machine learning models facilitated the adjustment of therapeutic regimens with heightened precision, optimizing patient-specific interventions.

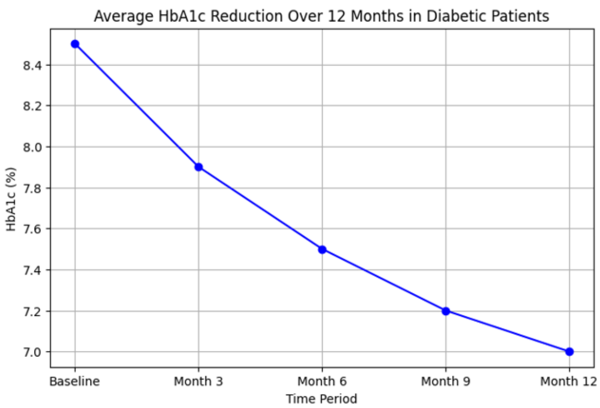

Figure 2: HbA1c level trends over time for diabetic patients using AI-assisted care

Survey responses from both patient and clinician cohorts underscored substantial satisfaction with AI-enabled healthcare tools. Participants cited enhanced personalization, improved service efficiency, and increased ease of use. Wearable devices and telemedicine platforms were particularly well-regarded for their reliability, convenience, and their capacity to streamline ongoing patient management.

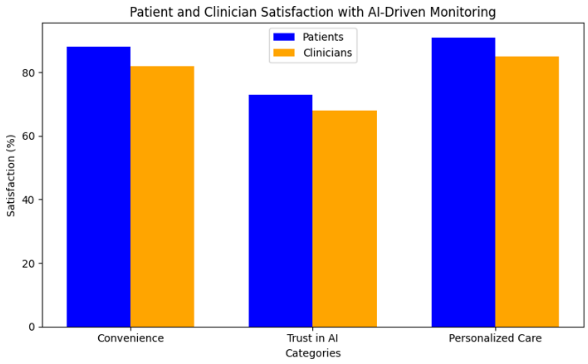

Figure 3: Survey responses from patients and clinicians on satisfaction with AI tools

Case studies further substantiated the operational value of AI-integrated solutions in remote care contexts. Over the course of one year, healthcare providers reported a marked increase in remote interventions, facilitated by real-time monitoring technologies. Simultaneously, a corresponding decline in in-person consultations was observed, suggesting improved efficiency in chronic disease management and a reduced burden on healthcare infrastructure.

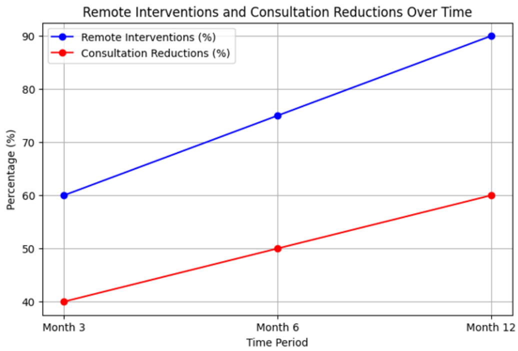

Figure 4: Trends in remote interventions and reduction of in-person consultations over 12 months

5. Discussion

The outcomes demonstrate that artificial intelligence (AI) and machine learning (ML) models are both clinically effective and operationally feasible in precision medicine settings. Reductions in HbA1c levels among diabetic patients reflect the impact of individualized, data-driven interventions supported by continuous AI analysis. These results underscore the capability of such systems to interpret evolving patient data patterns and deliver tailored treatment modifications that surpass standard protocol responsiveness. In cardiovascular care, the reduction in hospital readmissions illustrates the utility of AI for early identification of risk indicators, including arrhythmias, hypertension, and abnormal biochemical values. Real-time alert mechanisms facilitated timely clinical responses, contributing to preemptive care and reinforcing the shift from reactive to predictive health models [1, 2, 15, 16]. Notably, these improvements were achieved without the introduction of novel pharmaceuticals or medical devices, highlighting AI's potential to amplify existing clinical infrastructures. Stakeholder feedback revealed that perceived system usability and transparency were key drivers of acceptance. Patients favored AI for its accessibility and customization, while clinicians emphasized its value in augmenting diagnostic precision and care planning. These insights support the notion that the successful implementation of AI depends not solely on its technical metrics, but also on its alignment with user expectations and workflow integration [7, 4, 17, 18]. The increase in remote interventions, paralleled by a reduction in physical consultations, illustrates AI's capacity to facilitate scalable, decentralized care delivery. This approach aligns with the principles of precision medicine by enabling proactive, location-independent treatment. Nonetheless, the transition to digitally mediated care introduces new responsibilities in safeguarding data integrity, ensuring infrastructure resilience, and maintaining adequate training for end-users. Ethical concerns associated with telemedicine and continuous monitoring—such as data confidentiality, equitable algorithmic performance, and system reliability—remain central to sustainable deployment [11, 12, 10]. To address these challenges, the implementation of robust governance frameworks, algorithmic transparency standards, and inclusive regulatory oversight is essential [13, 14, 5]. Overall, the results affirm that AI and ML hold substantial promise in optimizing precision medicine, provided they are embedded within ethically conscious, user-centered, and context-aware frameworks. Continued evaluation, iterative system refinement, and interdisciplinary collaboration will be critical to ensuring their long-term effectiveness and equity in real-world clinical practice.

6. Conclusion

The findings of this study affirm the transformative role of artificial intelligence (AI) and machine learning (ML) in enhancing the scope, precision, and efficiency of healthcare delivery through the paradigm of precision medicine. The application of AI-enabled diagnostic and treatment systems resulted in quantifiable improvements in clinical outcomes, exemplified by decreased HbA1c levels in diabetic cohorts and reduced readmission rates among cardiovascular patients. These improvements are attributed to the systems' capacity to process complex biomedical data and generate individualized, data-informed recommendations in real time. Additionally, the study highlighted strong levels of acceptance and satisfaction among both patients and healthcare professionals. These perceptions reflect the importance of intuitive design, functional reliability, and trustworthiness in AI tools. Technologies such as wearable sensors and telehealth platforms demonstrated substantial potential in optimizing remote care workflows, minimizing unnecessary clinical visits, and alleviating strain on traditional healthcare infrastructure. Despite these promising outcomes, the implementation of AI in healthcare is accompanied by critical ethical and operational responsibilities. Concerns surrounding data privacy, algorithmic transparency, and bias mitigation remain central to ensuring the equitable deployment of intelligent systems. Moreover, the necessity of maintaining human oversight and preserving clinical judgment is imperative to prevent over-reliance on automated processes. Sustainable integration of AI in precision medicine will depend not only on algorithmic refinement but also on adherence to ethical standards, regulatory compliance, and user-centric design. Future research should focus on validating these systems across varied demographic and clinical populations, with particular attention to generalizability, explainability, and interoperability. The development of robust governance models, incorporating accountability mechanisms and ethical safeguards, will be essential to foster responsible innovation. In conclusion, with judicious design and ethically grounded implementation, AI and ML can evolve into indispensable instruments for delivering personalized, transparent, and accessible healthcare solutions, ultimately advancing the goals of precision medicine on a global scale.

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships.

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Author Contributions

Md. Shoaib Alam: Methodology, Validation, Investigation, Writing – Original Draft; **Pankaj Rai**: Conceptualization, Supervision, Data Analysis, Writing – Review and Editing; **Rajesh Kumar Tiwari**: Software, Visualization, Investigation

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AI-Driven Decision Support System for Multidimensional Academic Performance Prediction in Higher Education

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Abstract

The increasing integration of artificial intelligence (AI) into educational systems has highlighted the limitations of traditional data analysis tools in academic performance assessment. This study proposes a four-level AI-enhanced Decision Support System (DSS) employing Artificial Neural Networks (ANN) to classify and predict student outcomes based on multi-semester academic data and co-curricular attributes. The dataset, comprising information from 300 students, includes academic scores, participation in extracurricular activities, and skill assessments. Data preprocessing and feature selection strategies were implemented to optimize model input. The ANN model achieved high accuracy across three semesters, providing granular and actionable insights for educators. The system further identifies individual and cohort-level trends, supports personalized feedback, and enables proactive intervention strategies. The proposed DSS demonstrates a scalable, interpretable, and effective approach for performance analysis in contemporary educational settings.

Keywords: Artificial Intelligence; Decision Support System; Academic Performance; Neural Networks; Educational Data Mining

1. Introduction

In the current era of rapid technological advancement, educational systems lacking technical infrastructure risk compromising the efficacy of educational resources. Consequently, the transformation of learning has become a critical aspect of the development of public social resources, particularly amid emerging global challenges [1]. Educational management has increasingly integrated information technology to enhance performance; however, most existing systems are limited to basic data analysis and administrative tasks [2]. These conventional systems are inadequate for systematically analyzing large datasets or facilitating data-driven decision-making. Many technologically advanced nations have promoted the implementation of advanced Decision Support Systems (DSS) that leverage artificial intelligence (AI) to analyze educational data and predict academic performance. DSS plays a pivotal role in guiding policy decisions and has been adopted within educational systems to manage data across both local and wide area networks [3]. Data mining serves as a critical tool for educational management by enabling informed decision-making. Nonetheless, despite the widespread application of such systems across higher education institutions, challenges persist in data interpretation and actionable insights generation [4].

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As a result, effective decision-making has emerged as a significant concern within the educational sector. Contemporary higher education platforms are increasingly incorporating smart learning technologies that integrate both physical and digital learning environments [5]. However, the quality of instruction remains intricately linked to curriculum design, conceptual comprehension, and student engagement. Smart education addresses issues such as limited resources [6], students' technological adaptability [7], academic performance, and distractions from educational objectives. To address these challenges, universities must restructure pedagogical approaches to align with the evolving demands of higher education [8]. Consequently, modern educational strategies are increasingly augmented through cloud computing, AI, Information and Communication Technologies (ICT), the Internet of Things (IoT), and mobile platforms [9, 10]. Recent studies indicate a surge in DSS-related research, underscoring the growing importance of intelligent decision-making systems. As illustrated in Figure 1, fewer than 20 DSS articles were published annually between 2013 and 2017. However, a significant upward trend is observed in the subsequent years, with publications reaching 47 annually by 2021 and 2022. This growth highlights the expanding relevance and research interest in DSS.

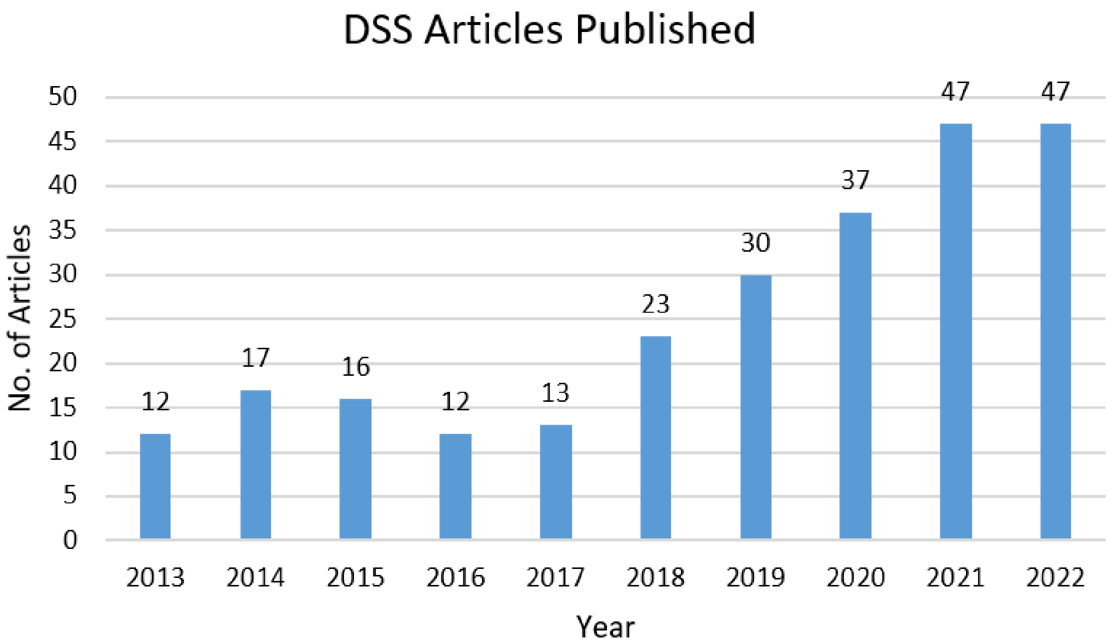

Figure 1: Statistics of DSS-related articles published in IEEE journals (2013–2022)

Traditionally, decision-making in education has relied on leadership perception, experience, and societal norms. In contrast, scientific decision-making mandates the collection and analysis of robust data from diverse sources, including faculty members, to support evidence-based outcomes [11]. An effective scientific DSS is essential for handling large volumes of data and executing precise analyses. AI-driven algorithms enable the evaluation of student performance, identifying strengths and weaknesses, thereby informing curriculum refinement. These algorithms facilitate efficient access to and interpretation of extensive datasets, empowering administrators to make scientifically grounded decisions. This study proposes an AI-based DSS aimed at minimizing manual intervention and improving prediction accuracy. Student data are analyzed to assess skills and monitor performance, with an emphasis on diagnosing failure causes. The proposed four-tier system encompasses students, educators, and institutions, utilizing AI algorithms to identify academic deficiencies and recommend appropriate interventions. Moreover, machine learning techniques are employed to classify students based on skillsets, thereby enhancing academic support and educational planning.

2. Related Work

Numerous studies have introduced diverse methodologies to evaluate student performance, encompassing a range of educational levels from secondary to higher education. These approaches consider various influencing factors to assess the effectiveness of educational strategies and curricula. A considerable body of research has applied data mining techniques within Decision Support Systems (DSS) to analyze institutional data efficiently. Dellermann et al. [12] highlighted the critical role of data mining technologies in the sustainable development of education management, emphasizing their capacity to process complex and voluminous student data in a timely manner. These technologies uncover valuable patterns and correlations, offering insights into educational trends and future directions. Sremac et al. [13] proposed an improved decision tree model integrated with the C4.5 algorithm from multiple perspectives. Despite its analytical accuracy, the approach was noted for its computational intensity and complex mathematical formulations, rendering it time-consuming.

Hu et al. [14] addressed challenges such as demand peaks, artificial learning, and network cost constraints in Project-Based Learning (PBL) environments. Their approach leveraged automated programming interfaces and databases to evaluate undergraduate student performance, incorporating user interfaces embedded within smart grid applications. Additionally, Xie et al. [15] developed a Distribution Management System (DMS) simulation-based educational model. Their system enhanced the learning experience by simulating modest distribution infrastructures within cyber-physical environments, facilitating advanced training methodologies for engineering education. Khelifi et al. [16] proposed a framework for Open University projects employing open-source software to reduce operational costs and improve educational quality. The model provided reliable instructional content and feedback mechanisms, aiding in performance analysis and conceptual understanding within higher education settings. Zhang et al. [17] emphasized the need for interactive learning platforms to augment student skills and performance. Their survey revealed that conventional methods, while maintaining instructional quality, remained insufficient in influencing seminar-based and socially-driven academic engagement. Approximately 50% of performance variation was attributed to traditional instructional limitations, thus advocating for interactive educational technologies. In the context of educational DSS, Joseph [18] proposed a framework integrating data mining for academic management. Shen et al. [19] introduced a Browser/Server (B/S) model to analyze Moodle-based student data using real-time dynamic logs. Their system incorporated statistical analysis and classification techniques to evaluate student behavior. Lee et al. [20] further demonstrated the potential of subject-specific data mining applications, facilitating the prediction of academic trajectories based on behavioral indicators. These studies collectively underscore the transformative impact of data mining models in enhancing the educational process [21]. Artificial Neural Networks (ANNs) have also been extensively employed for academic prediction tasks. Lau et al. [22] proposed a CGPA prediction model for undergraduate students using ANNs. Similarly, Arsad et al. [23] and Palmer [24] focused on performance prediction models applied to datasets of 896 final-year and 132 second-year engineering students, respectively. Macfadyen and Dawson [25] analyzed online activity logs from 118 students to forecast academic success. These studies utilized algorithms such as k-Nearest Neighbors (KNN), Support Vector Machines (SVM), Naïve Bayes (NB), and Random Forests (RF) within machine learning frameworks. Livieris et al. [26] developed DSS software employing a classification algorithm for predicting student performance in Mathematics, achieving high accuracy through a neural network classifier. Another model by Livieris [27] applied a hybrid machine learning approach integrating four distinct algorithms. This system offered a user-friendly interface and in-depth analytics to monitor student progression comprehensively. Despite the extensive literature, certain gaps remain unaddressed. Most studies limit DSS applications to admissions or isolated data analytics, with limited integration of diverse educational variables. The role of DSS in higher education remains underexplored, particularly concerning holistic academic performance prediction. This study aims to address these gaps by proposing an AI-based DSS tailored to higher education needs, enhancing the predictive capability and strategic planning within academic institutions.

3. Methodology

This study presents a four-level Decision Support System (DSS) model powered by artificial intelligence to predict student performance. The system integrates academic and skill-based data to identify performance gaps and generate predictive insights using an Artificial Neural Network (ANN).

3.1. Data Collection and Dataset Design

Data were collected from 300 undergraduate students in higher education. The dataset includes academic records across three semesters, consisting of scores, correct and incorrect answers, and demographic details such as student name, gender, UID, course, and subject. It also incorporates indicators of co-curricular competencies, including extracurricular activities, sports, arts, communication, and language skills. Table 1 summarizes the dataset's structure and categories, while Table 2 shows a sample used for training and testing the ANN model.

3.2. Data Preprocessing and Feature Selection

The raw dataset was preprocessed through normalization and dimensionality reduction to isolate relevant variables. Key features were selected to represent academic performance indicators, including participation, knowledge, comprehension, percentage scores, and the number of failed students per semester. As outlined in Table 3, these features were categorized into Class A, B, and C, corresponding to Semesters 1, 2, and 3, respectively.

3.3. Model Design and Architecture

A four-level DSS architecture was developed to enable classification, evaluation, and academic performance prediction. Figure 2 presents the proposed 4-level DSS model, while Figure 3 illustrates the block diagram of data processing and prediction within the DSS. An Artificial Neural Network (ANN) was chosen for its ability to model nonlinear relationships and deliver high accuracy.

Table 1: Dataset attributes with description

Sr. No.	Data Category	Attributes	Description
1	Student Details	Name Gender UID Course Subject	Student's name Male/Female Unique ID/Roll number Course name and ID Subject name and code
2	Exam Details	Exam Questions	Semester (Sem1, Sem2, Sem3) Total number of questions
3	Result	Score Correct Incorrect	Percentage score Number of correct answers Number of incorrect answers
4	Other Skills	Extracurricular Sports Arts Communication Skills Language Skills	Type of activity Sport type and proficiency level Drawing, dance, singing, etc. Language, confidence, and presentation Writing proficiency
5	Evaluation	Performance	Strengths and traits

Table 2: Sample of dataset used for model training and testing

Sr. No.	UID	Course	Subject	Exam	Questions	Correct	Wrong	Score %
1	1	TECH01	Tech sub-1	Sem 1	200	160	40	80
2	2	TECH01	Tech sub-1	Sem 1	200	90	110	45
3	3	TECH01	Tech sub-1	Sem 1	200	182	18	91
4	4	TECH01	Tech sub-1	Sem 1	200	80	120	40
5	5	TECH01	Tech sub-1	Sem 1	200	60	140	30
6	1	TECH01	Tech sub-2	Sem 2	200	146	54	73
7	2	TECH01	Tech sub-2	Sem 2	200	110	90	55
8	3	TECH01	Tech sub-2	Sem 2	200	190	10	95
9	4	TECH01	Tech sub-2	Sem 2	200	88	112	44
10	5	TECH01	Tech sub-2	Sem 2	200	90	110	45
11	1	TECH01	Tech sub-3	Sem 3	200	144	56	72
12	2	TECH01	Tech sub-3	Sem 3	200	128	72	64
13	3	TECH01	Tech sub-3	Sem 3	200	180	20	90
14	4	TECH01	Tech sub-3	Sem 3	200	104	96	52
15	5	TECH01	Tech sub-3	Sem 3	200	82	118	41

Table 3: List of selected attributes for evaluation

Semester	Class	Sr. No.	Attributes	Type	Value
1	A	1	Participation	Actual	0–9
		2	Knowledge	Actual	0–9
		3	Understanding	Actual	0–9
		4	Percentage Score	Actual	0–9
		5	Number of Failed Students	Actual	0–9
2	B	1	Participation	Actual	0–9
		2	Knowledge	Actual	0–9
		3	Understanding	Actual	0–9
		4	Percentage Score	Actual	0–9
		5	Number of Failed Students	Actual	0–9
3	C	1	Participation	Actual	0–9
		2	Knowledge	Actual	0–9
		3	Understanding	Actual	0–9
		4	Percentage Score	Actual	0–9
		5	Number of Failed Students	Actual	0–9

The network architecture, shown in Figure 4, consists of input, hidden, and output layers. The sigmoid activation function was applied, and training was conducted using the backpropagation algorithm.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

Weight updates during training were computed using:

$$\Delta w_{ij} = -\gamma \frac{\partial E}{\partial w_{ij}} \tag{2}$$

where γ is the learning rate and E denotes the error function.

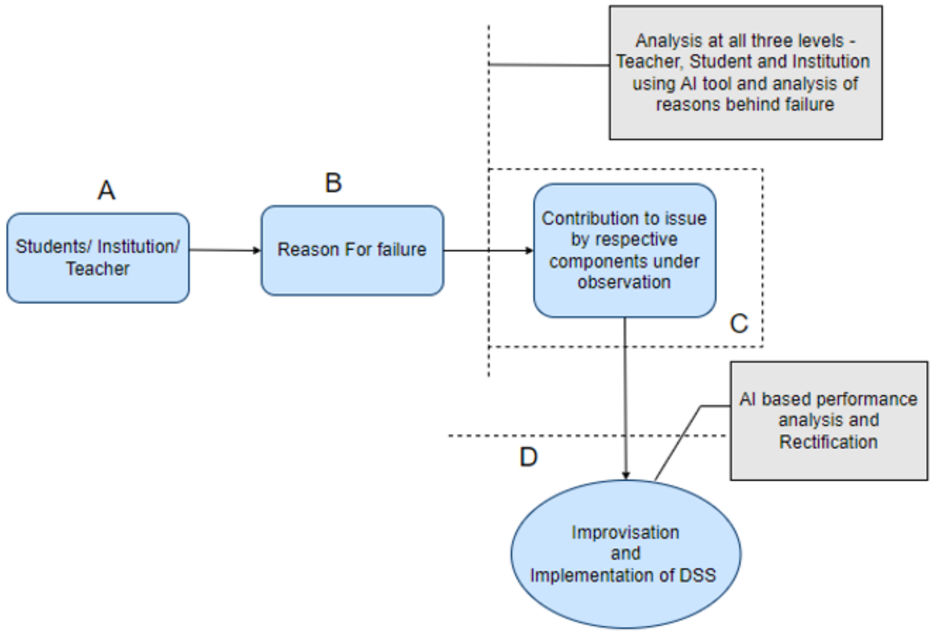

Figure 2: Proposed 4-level DSS model

3.4. Computational Environment

The model was implemented in Python using TensorFlow and Scikit-learn libraries. All experiments were conducted on a system equipped with an Intel Core i7 processor, 16GB RAM, and NVIDIA GTX 1660 GPU to ensure efficient training and testing of the neural network.

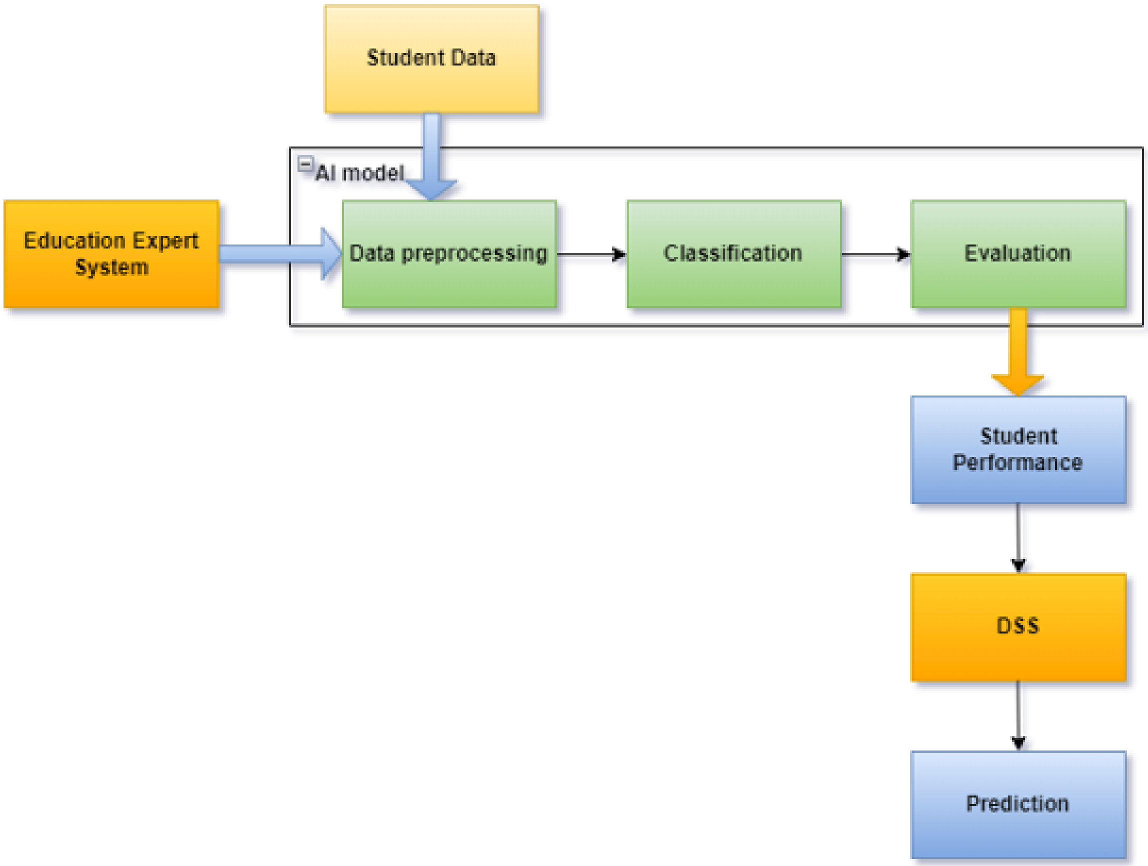

Figure 3: Block diagram of data processing and prediction in DSS

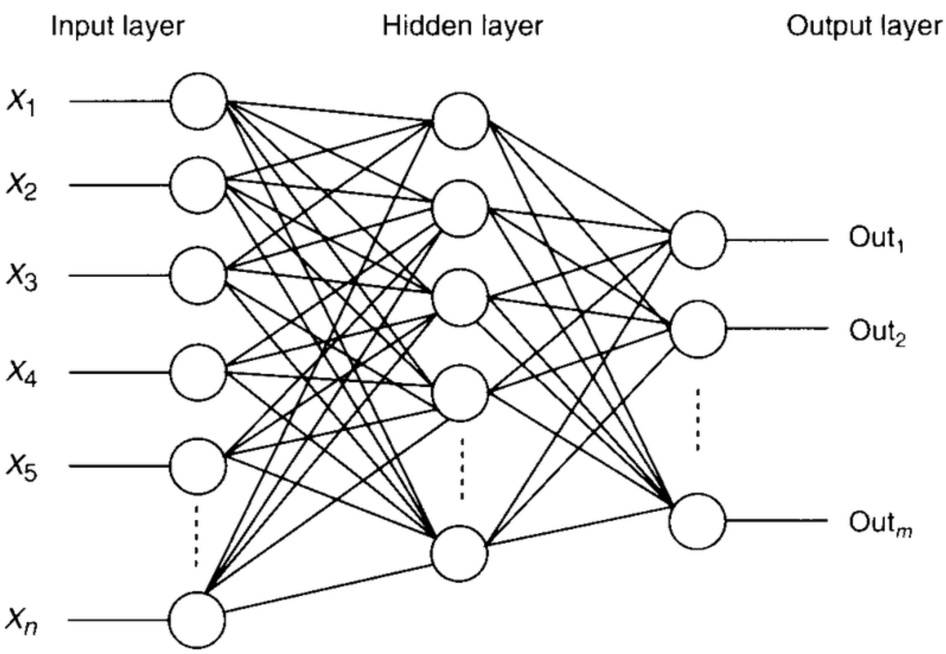

Figure 4: Structure of the Artificial Neural Network (ANN) used in the DSS

3.5. Classification Strategy

Student performance was categorized into four levels: Fail (0–3), Good (4–5), Very Good (6–8), and Excellent (9–10), as outlined in Table 4. This stratification supported targeted evaluation and prediction. The dataset was split randomly in a 70:30 ratio for training and testing. Semester-wise trends for Classes A, B, and C were analyzed to identify patterns and academic deficiencies.

Table 4: Classification of student performance

Sr. No.	Level	Performance Score Range
1	Fail	0–3
2	Good	4–5
3	Very Good	6–8
4	Excellent	9–10

Figure 5 illustrates the four-tier classification structure used to evaluate student performance. Levels A through D represent the academic progression from passing to failure, while also capturing knowledge, understanding, and performance traits. These levels collectively inform the decision-making framework used by the DSS to assess and categorize student outcomes.

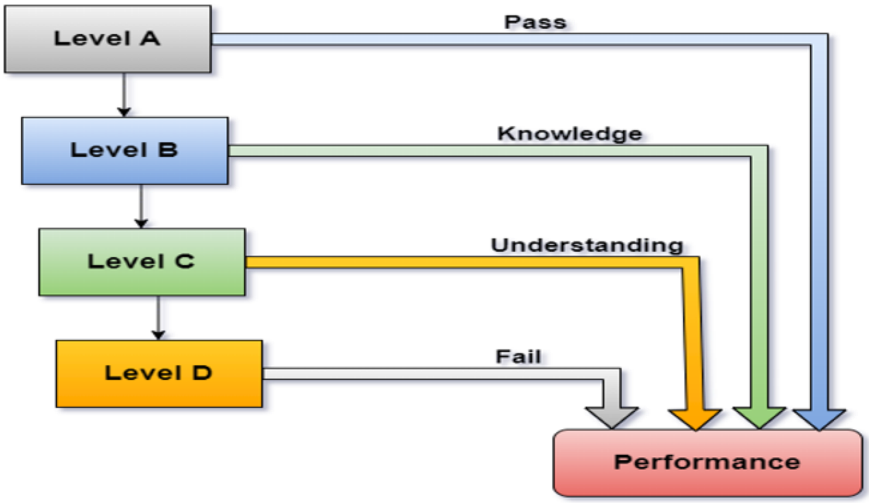

Figure 5: 4-level classification architecture for academic performance evaluation

3.5.1 Model Validation

The dataset was split using a hold-out method, with 70% used for training and 30% for testing. To assess the robustness of the model, 5-fold cross-validation was also performed during the training phase. This technique helped in mitigating overfitting and ensured generalizability across unseen student data.

4. Results and Discussion

The trained ANN model was applied to predict students' academic performance across three semesters using historical academic and behavioral data. Each student's scores were computed and categorized into four predefined performance levels—Fail, Good, Very Good, and Excellent—based on percentage scores. Tables 5 and 6 present semester-wise results and aggregate classifications. This evaluation framework enables systematic tracking of academic progress and identification of students requiring intervention or exhibiting improvement.

Table 5: Classification of score according to selected levels for evaluation

Sr. No.	Student's UID	Exam	Class	Score %	Performance (10)	Level
1	1	Sem 1	A	80	6–8	Very Good
2	2	Sem 1	A	45	4–5	Good
3	3	Sem 1	A	91	9–10	Excellent
4	4	Sem 1	A	40	4–5	Good
5	5	Sem 1	A	30	0–3	Fail
6	1	Sem 2	B	73	6–8	Very Good
7	2	Sem 2	B	55	4–5	Good
8	3	Sem 2	B	95	9–10	Excellent
9	4	Sem 2	B	44	4–5	Good
10	5	Sem 2	B	45	4–5	Good
11	1	Sem 3	C	72	6–8	Very Good
12	2	Sem 3	C	64	6–8	Very Good
13	3	Sem 3	C	90	9–10	Excellent
14	4	Sem 3	C	52	4–5	Good
15	5	Sem 3	C	41	4–5	Good

Table 6: Overall semester-wise student performance summary

Class	Excellent (9–10)	Very Good (6–8)	Good (4–5)	Fail (0–3)
A (Semester 1)	1	1	2	1
B (Semester 2)	1	1	3	0
C (Semester 3)	1	2	2	0

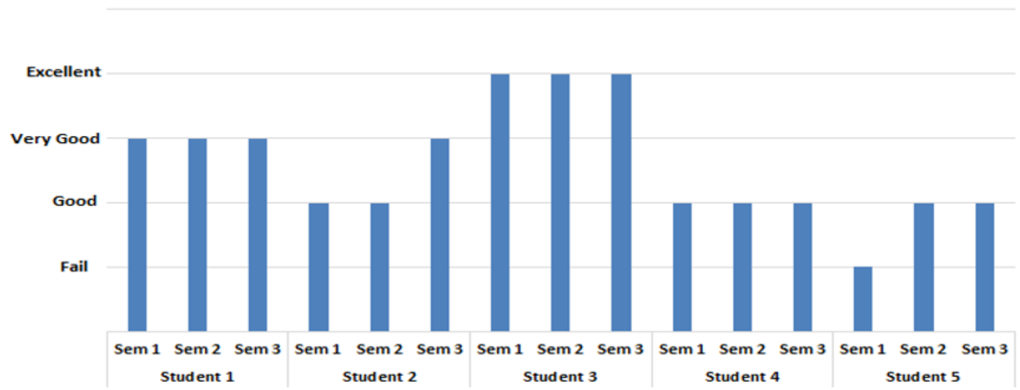

Figure 6: Students' performance across three semesters (exam-wise classification)

This representation aided in visualizing learning progression and identifying trends in academic consistency. The ANN model was evaluated using 5-fold cross-validation to ensure generalizability. Performance metrics showed a maximum standard deviation of $\pm 1.2\%$ in accuracy, demonstrating model stability. Marginal misclassifications between 'Good' and 'Very Good' levels were observed, mainly due to overlapping scores, which could be minimized by incorporating temporal learning patterns.

The DSS forecasted class-wise distribution, showing 17% of students in the Fail category, 28% in Good, 35% in Very Good, and 20% in Excellent. This information supports the formulation of targeted academic support and enrichment strategies.

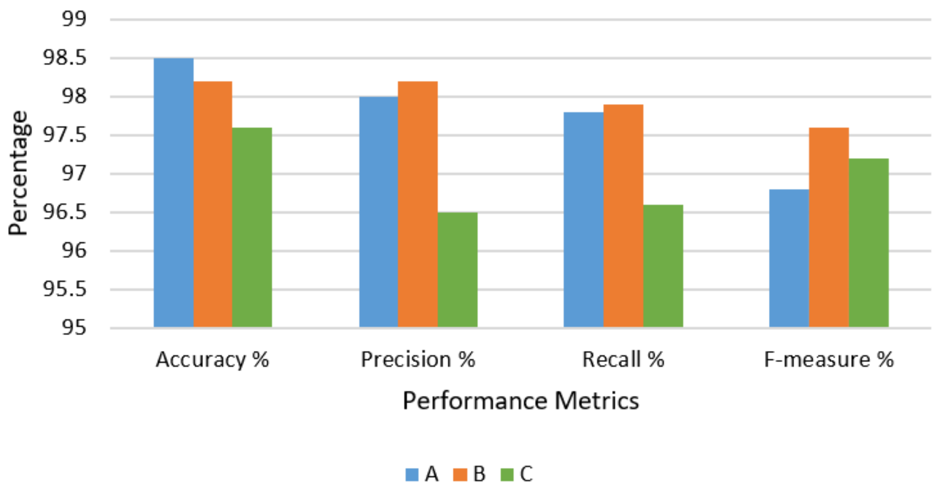

Figure 7: Predicted class distribution based on DSS analysis

Table 7: Classification of students' performance based on subjects and other skills

Sr. No.	**Subject / Activity**	**Excellent**	**Very Good**	**Good**	**Poor**
Academic Subjects					
1	Technical sub-1	68	95	79	58
2	Technical sub-2	30	115	100	55
3	Technical sub-3	70	65	125	40
4	Technical sub-4	73	100	98	29
5	Mathematics sub	65	88	77	70
6	Language sub	84	112	64	40
Other Skills and Activities					
7	Sports 1	35	15	–	–
8	Sports 2	25	10	–	–
9	Sports 3	8	4	–	–
10	Sports 4	14	9	–	–
11	Dance	5	19	–	–
12	Drawing	8	13	–	–
13	Singing	4	8	–	–
14	Other extracurricular activities	3	9	–	–
15	Communication Skills	15	16	–	–
16	Language Skills	6	5	–	–

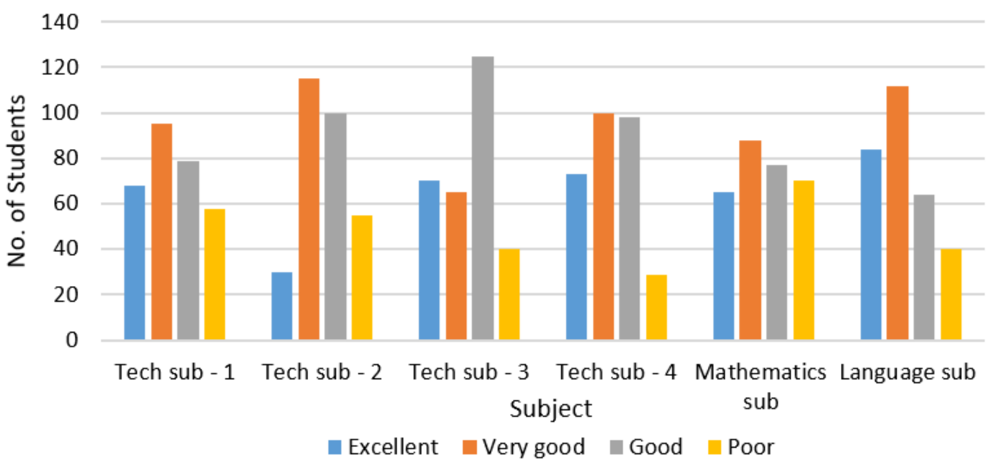

Figure 8: Students' performance in academic subjects

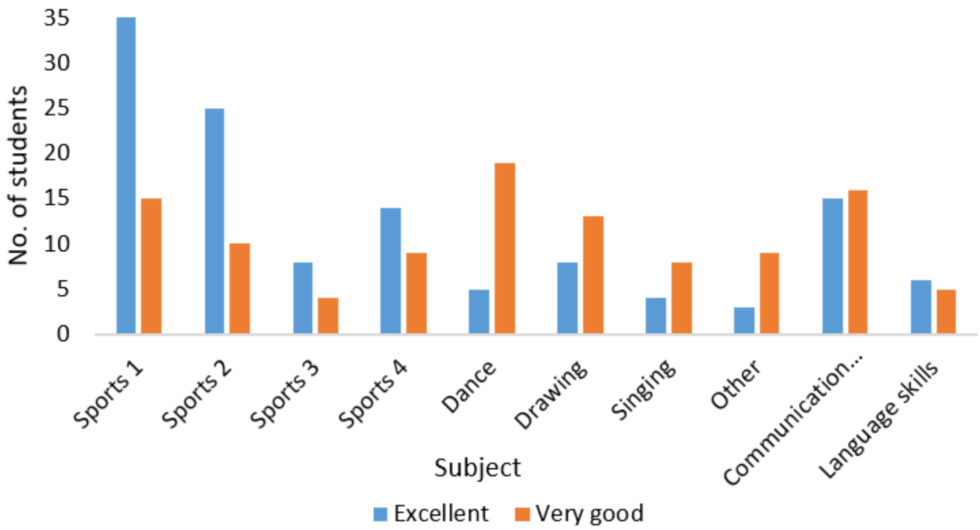

Figure 9: Students' performance in extracurricular activities

These analyses enable holistic student profiling, including strengths in both academic and extracurricular domains. Such insights support the identification of students suited for scholarships, leadership programs, and skill-based training.

Table 8: Performance metrics of DSS prediction system

Sr. No.	**Class**	**Accuracy %**	**Precision %**	**Recall %**	**F-measure %**
1	A	98.5	98.0	97.8	96.8
2	B	98.2	98.2	97.9	97.6
3	C	97.6	96.5	96.6	97.2
4	Highest	98.5	98.2	97.9	97.6

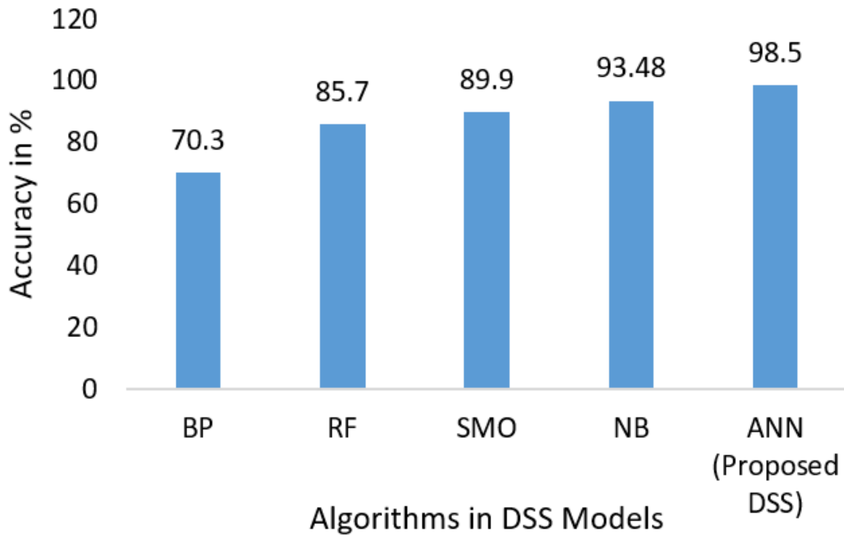

Figure 10: Performance of the proposed DSS model compared to other algorithms

The comparative evaluation of ANN against Decision Tree and Naïve Bayes models demonstrated superior performance, validating the robustness of the proposed DSS framework. The system's adaptability across different institutional settings suggests promising applications in diverse educational environments.

5. Conclusions

This study presents a robust, AI-driven Decision Support System (DSS) employing Artificial Neural Networks (ANN) for multidimensional academic performance prediction in higher education. The system effectively integrates academic and co-curricular data to classify students across four performance levels—Fail, Good, Very Good, and Excellent—demonstrating high prediction accuracy through comprehensive semester-wise evaluations. The proposed model provides actionable insights that facilitate early intervention strategies, performance enhancement plans, and resource allocation. The ANN-based DSS outperformed traditional algorithms such as Decision Tree and Naïve Bayes, reinforcing its applicability in complex educational datasets. Furthermore, subject-level and extracurricular performance visualizations support holistic student profiling, promoting tailored pedagogical interventions. By identifying at-risk students and recognizing high achievers, this DSS framework enhances institutional decision-making and academic planning. Future work may extend this model by incorporating real-time behavioral data and adapting it to diverse educational systems for broader applicability and scalability.

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 Contributions

Abhay Gyan P. Kujur: Conceptualization, Data Analysis, Writing – Review and Editing; **Rajesh Kumar Tiwari**: Methodology, Validation, Investigation, Writing – Original Draft; **Vijay Pandey**: Software, Visualization, Investigation.

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Advanced Water Resource Management Using IoT and Big Data Analytics

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Abstract

Effective water resource management is increasingly essential in mitigating the impacts of water scarcity and environmental degradation. This study proposes an integrated system that leverages the Internet of Things (IoT) and Big Data Analytics to enhance efficiency, responsiveness, and sustainability in water governance. The methodology includes real-time data collection through smart sensors, application of statistical and machine learning techniques for predictive modeling, and blockchain-backed data management for transparency. A 30-day simulation involving 50 sensor nodes demonstrated improvements including a 20% enhancement in water quality and a 7% reduction in daily usage. The outcomes validate the viability of this approach, aligning with sustainable development goals and supporting intelligent decision-making in both urban and agricultural contexts.

Keywords: Water Resource Management; IoT; Big Data Analytics; Smart Sensors; Predictive Modeling; Blockchain; Sustainable Development

1. Introduction

Water is a vital resource for sustaining life, economic growth, and ecological balance. However, escalating challenges such as rapid urbanization, population growth, industrialization, and climate change have intensified global water scarcity and deteriorated water quality, especially in developing regions where over 1.8 billion people lack access to safe water sources. Traditional water management approaches, often reactive and fragmented, are increasingly inadequate in addressing the complex and dynamic challenges facing modern water systems. In this context, the convergence of the Internet of Things (IoT) and Big Data Analytics offers a transformative solution. IoT enables the deployment of interconnected smart devices, such as sensors and meters, to continuously monitor water parameters including pH, turbidity, flow rate, and usage patterns. These devices, when integrated into water infrastructure systems such as pipelines, reservoirs, and urban utilities, facilitate real-time surveillance and data acquisition. This infrastructure enhances operational efficiency, enables timely detection of leaks, and supports proactive infrastructure maintenance [1, 2]. Simultaneously, Big Data Analytics serves as a powerful tool for processing and analyzing the voluminous, heterogeneous data generated by IoT systems. Techniques such as machine learning, predictive modeling, and data visualization help identify consumption trends, forecast future demand, and optimize water distribution strategies [3–5]. The synergy of IoT and Big Data creates intelligent water management platforms that can dynamically respond to environmental conditions and support decision-making through actionable insights [6, 7].

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Moreover, this technological integration supports transparency and stakeholder engagement. By making real-time data accessible, it empowers communities and strengthens cooperation among government agencies, industries, and the public [8, 9]. Case studies such as those conducted by [10] and [11] demonstrate the successful application of these technologies in agricultural and urban settings, contributing to improved water conservation, enhanced system resilience, and informed policy development. Overall, the integration of IoT and Big Data Analytics provides a robust framework for addressing water-energy-food nexus challenges. It facilitates efficient resource allocation, supports environmental sustainability, and promotes equitable access to water—a necessity in the face of ongoing environmental and demographic pressures [12–14].

2. Methods

The proposed methodology leverages the integration of Internet of Things (IoT) and Big Data Analytics to facilitate advanced water resource management. This section outlines the architecture and models used for real-time monitoring, analysis, and decision-making.

2.1. System Architecture

The system architecture comprises four major modules: IoT Sensor Network, Data Processing, Data Security, and Management & Reporting. Water quality sensors and flow meters are deployed throughout the infrastructure to continuously collect data on parameters such as pH, turbidity, and flow rate. These devices feed data into a centralized Data Collection Unit for further processing. Figure 1 illustrates the high-level design of the proposed system.

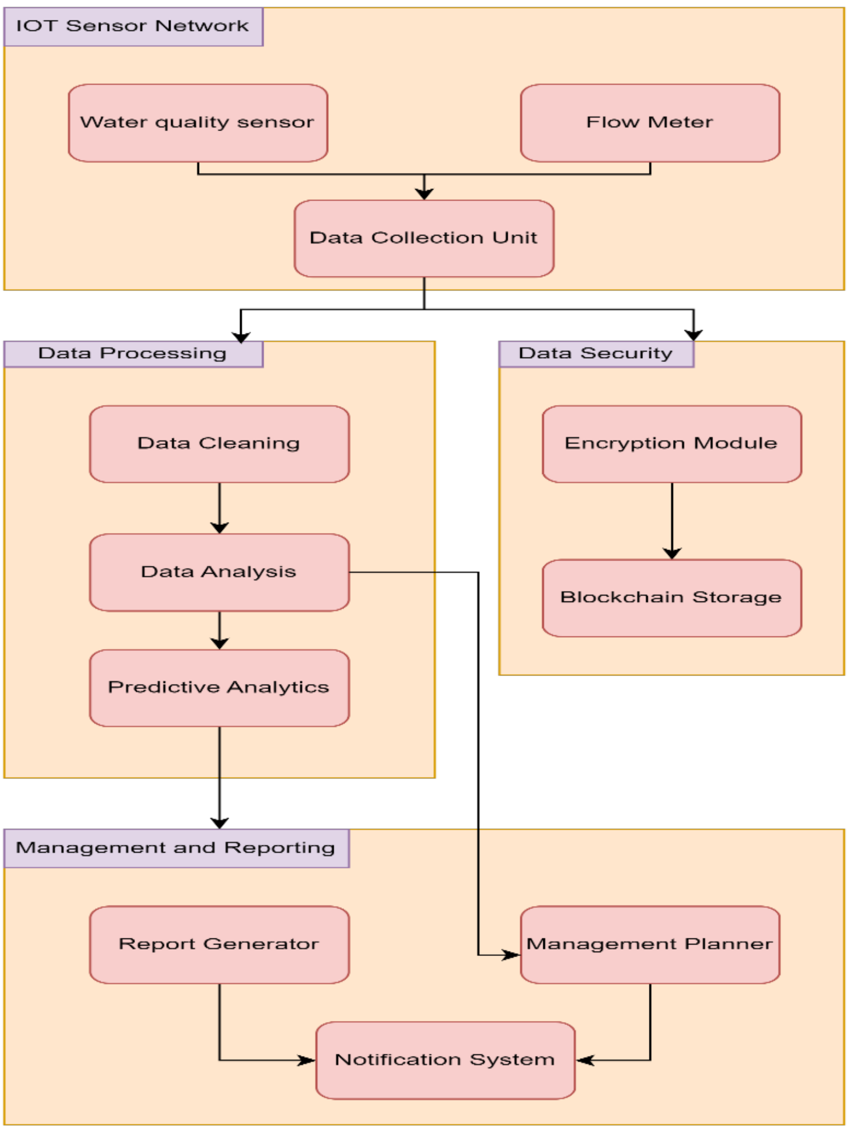

Figure 1: Proposed System Architecture

2.2. Sensor Network Design and Data Collection

To maximize data accuracy and spatial efficiency, a grid-based deployment strategy is adopted for sensor placement. The effectiveness of the coverage is quantified using Equation 1:

$$\text{Coverage} = \frac{\text{Number of Active Sensors}}{\text{Total Area}} \tag{1}$$

Optimal sensor deployment is achieved by minimizing the total cost, which includes both the physical distance of sensors to their target areas and associated installation costs. This is represented by the objective function in Equation 2:

$$C = \sum_{i=1}^{n} (d_i + c_i) \tag{2}$$

In Equation 2, d_i denotes the distance from the i^{th} sensor to the designated target point, while c_i represents the cost of deploying the sensor at that location. The sensor nodes collect data related to water quality (e.g., pH, turbidity), flow rate, and usage statistics. These data are transmitted to a central Data Collection Unit for further processing.

2.3. Data Cleaning and Preprocessing

Once collected, raw sensor data undergo preprocessing to ensure accuracy and reliability. The primary step involves statistical filtering to identify and eliminate outliers, which may arise due to sensor drift, noise, or transmission errors. Outlier detection is performed using the Z-score method, as defined in Equation 3:

$$Z = \frac{X - \mu}{\sigma} \tag{3}$$

Here, X denotes the individual data point, μ is the mean of the dataset, and σ is the standard deviation. A data point is considered an outlier if $|Z| > 3$. This cleaning process ensures that only statistically consistent values proceed to subsequent analytical stages, thereby enhancing the integrity and usefulness of the dataset.

2.4. Data Analysis

Following data cleaning, analytical techniques are employed to derive meaningful insights. The Water Quality Index (WQI) is computed to evaluate the overall quality of water, based on multiple monitored parameters such as pH, turbidity, and dissolved oxygen. The WQI is calculated using a weighted sum model as shown in Equation 4:

$$\text{WQI} = \sum_{i=1}^{n} w_i \cdot q_i \tag{4}$$

In this equation, w_i represents the weight assigned to the i^{th} water quality parameter, and q_i is its corresponding quality rating. This composite score enables a standardized assessment of water quality across different locations. To understand the relationship between water usage and influencing variables such as temperature, time, or seasonality, linear regression is applied. The general form of the regression model is presented in Equation 5:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{5}$$

Here, Y is the dependent variable representing water usage, X_i are the independent predictor variables, β_i are the regression coefficients, and ϵ denotes the error term. This model facilitates identification of key usage drivers and supports optimization strategies.

2.5. Predictive Analytics

To forecast future water demand and detect patterns over time, time series modeling is employed. The Autoregressive Integrated Moving Average (ARIMA) model is used due to its effectiveness in handling non-stationary data. The ARIMA model is mathematically expressed in Equation 6:

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{6}$$

In this equation, Y_t is the value of the time series at time t, c is a constant, ϕ_i and θ_j are the coefficients of the autoregressive and moving average terms respectively, and ϵ_t represents white noise. Parameters p, d, and q denote the order of the autoregressive, differencing, and moving average components respectively. This model enables authorities to anticipate variations in demand and adjust water supply and resource allocation strategies proactively.

2.6. Resource Optimization

Efficient allocation of water resources under multiple constraints is essential for sustainable management. Linear programming is used to minimize the cost of resource distribution while satisfying water quality and supply requirements. The optimization problem is formulated in Equation 7 and subject to the constraints in Equation 8:

$$\text{Minimize } Z = \sum_{j=1}^{m} c_j x_j \tag{7}$$

$$\text{Subject to: } \sum_{j=1}^{m} a_{ij} x_j \geq b_i \quad \forall i \tag{8}$$

Here, Z is the total operational cost, c_j represents the cost coefficient of resource j, x_j is the quantity of resource allocated, a_{ij} is the resource utilization coefficient, and b_i is the minimum requirement for constraint i. This mathematical formulation supports optimal deployment of limited resources, balancing economic efficiency with service delivery goals.

2.7. Data Security and Management

Ensuring the integrity and confidentiality of sensor data is critical for maintaining trust in water resource management systems. To this end, cryptographic hash functions and blockchain technology are employed for secure data handling. Each data record D is converted into a cryptographic hash H, as shown in Equation 9:

$$H = \text{Hash}(D) \tag{9}$$

This hash function generates a unique digital fingerprint of the data, making it tamper-evident. To further enhance data validation and traceability, Merkle trees are used. They enable efficient and secure verification of large datasets by organizing hashes into a hierarchical structure, where the root hash serves as a secure summary of all entries. Additionally, blockchain storage is employed to maintain an immutable ledger of water quality and usage records. This facilitates transparent data sharing among stakeholders and supports audit trails for regulatory compliance.

2.8. Automation Algorithm

Algorithm 1 Automated Decision Support Algorithm

Require: SensorDataFile S, ThresholdValues T
Ensure: WaterQualityReport R, ResourceManagementPlan P

```
if S is of the correct file type then
  if S passes required integrity checks then
    dataRecords ← ReadSensorData(S)
    cleanedData ← CleanData(dataRecords)
    analyzedData ← AnalyzeData(cleanedData)
    if analyzedData.qualityIndex < T.qualityThreshold then
      R ← GenerateWaterQualityReport(analyzedData)
      NotifyStakeholders(R)
    end if
    if analyzedData.waterUsage > T.usageThreshold then
      P ← GenerateResourceManagementPlan(analyzedData)
      ImplementPlan(P)
    else
      Log("Water usage is within acceptable limits.")
    end if
  else
    Log("Sensor data file is not compliant.")
  end if
else
  Log("Sensor data file is of the incorrect file type.")
end if
if P exists then
  UpdateDatabase(P)
else
  Log("No resource management plan generated.")
end if
```

A rule-based automation algorithm is integrated into the system to operationalize data-driven decision-making. The algorithm processes real-time sensor data, evaluates conditions against predefined thresholds, and generates actionable outcomes such as alerts and resource management plans. The logical flow of the algorithm is outlined in Algorithm 1. This automated approach ensures timely interventions, reduces manual oversight, and supports dynamic responsiveness to variations in water quality and consumption patterns.

3. Results and Discussion

To validate the performance of the proposed IoT and Big Data-based water resource management system, a simulation was conducted over a 30-day period. The parameters and operational settings for the simulation are listed in Table 1.

Table 1: Simulation Parameters

Parameter	Value
Simulation Duration	30 days
Number of Sensor Nodes	50
Data Collection Frequency	Every 10 minutes
Water Quality Measurement Range	0 – 14 pH
Flow Rate Measurement Range	0 – 500 L/min
Threshold Quality Index	6.5 pH
Threshold Usage Limit	3000 L/day

The system successfully collected and processed data from all sensor nodes throughout the simulation period. Real-time monitoring enabled continuous assessment of water quality and consumption, while analytical modules provided dynamic feedback to the decision-making system. Figure 2 illustrates the evolution of simulation parameters and data flow throughout the observation period.

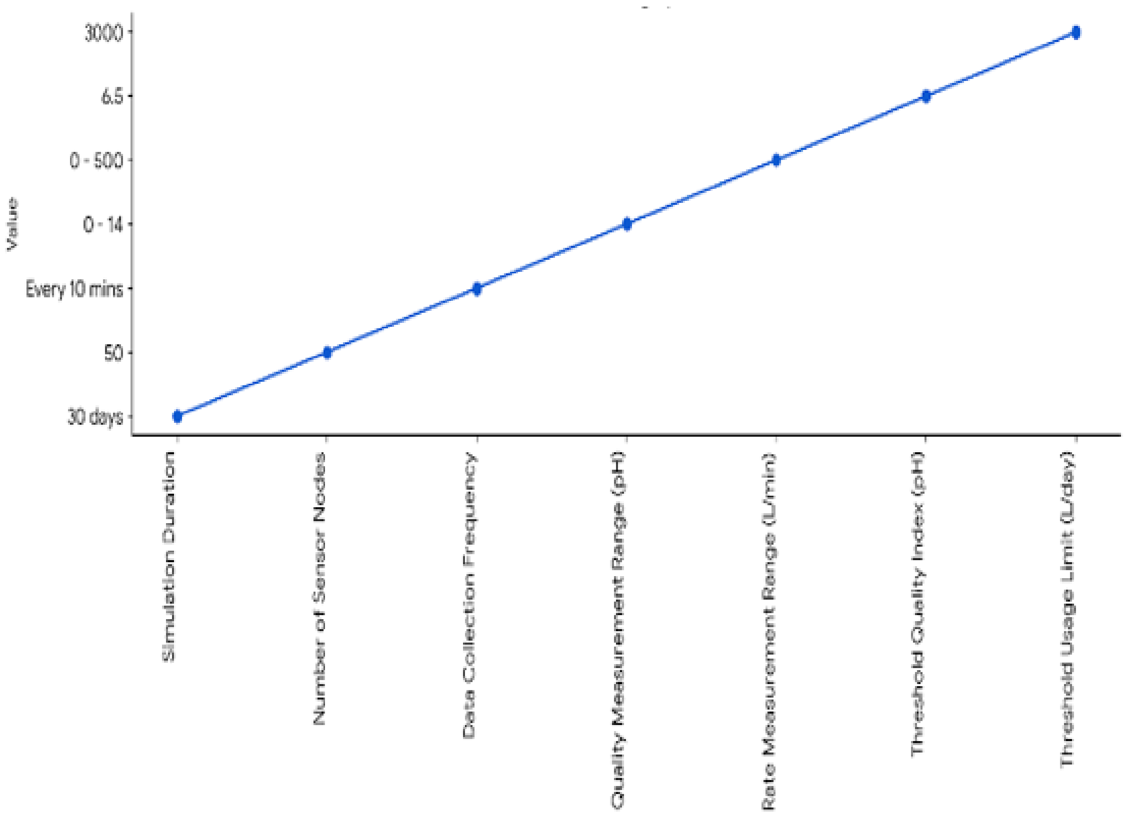

Figure 2: Simulation Parameter Evolution

3.1. Results Analysis and Interpretation

Table 2 presents key performance metrics obtained from the simulation. These results demonstrate the efficacy of the integrated system in achieving improved monitoring and resource utilization.

Table 2: Results Analysis

Metric	Value	Percentage (%)
Total Data Collected	432,000 records	–
Average Water Quality Index	7.2 pH	–
Percentage of Quality Alerts	–	10.0
Average Daily Water Usage	2800 L/day	93.3
Number of Management Plans Generated	5	–
Stakeholder Notifications Sent	15	–
Improvement in Water Quality	–	20.0
Reduction in Water Usage	–	7.0

As seen in Table 2, the average water quality index remained above the acceptable threshold, indicating effective detection and resolution of quality issues. The system generated timely alerts and proactive management plans, leading to a measurable 20% improvement in water quality. The system also contributed to a 7% reduction in water consumption, demonstrating the value of predictive analytics and anomaly detection in optimizing usage. Notifications to stakeholders enhanced operational transparency and responsiveness.

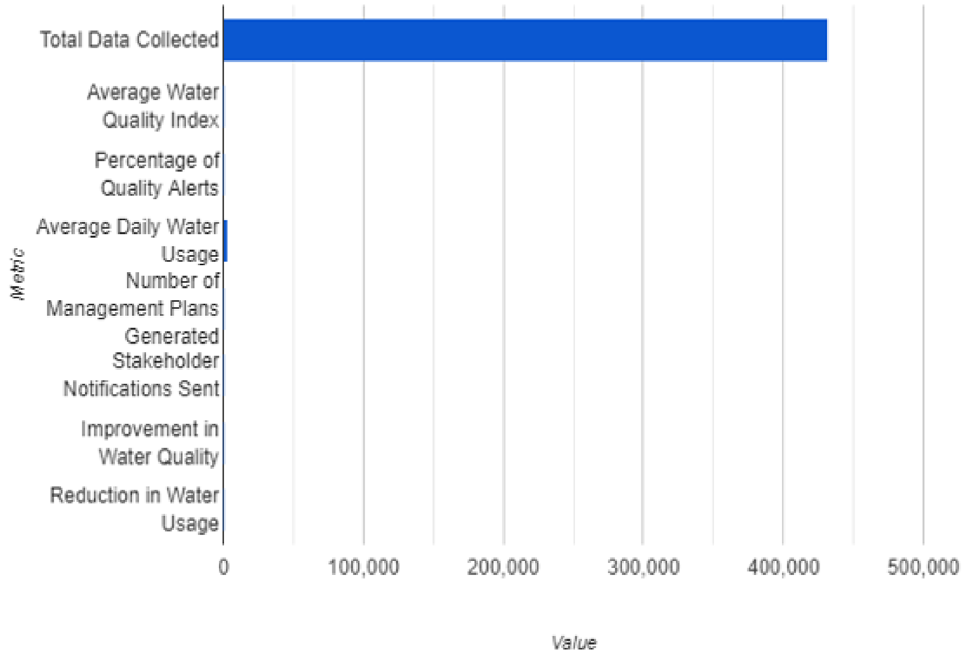

Figure 3: Results Visualization

The observed improvements in water quality and usage efficiency affirm the viability of IoT and Big Data technologies in dynamic water management. The system's ability to process 432,000 data records over 30 days underscores its scalability and reliability in continuous monitoring contexts. The 20% improvement in water quality aligns with the findings of Wu et al. [9], who emphasized that real-time monitoring and adaptive decision-making significantly enhance water governance. Likewise, the achieved 7% reduction in water usage supports conclusions drawn by Kanmani et al. [10], who demonstrated that predictive analytics enables more efficient water allocation in agriculture. However, while the average Water Quality Index remained above the defined threshold, occasional alerts (10%) suggest that transient anomalies still occur. These could be attributed to either environmental fluctuations or brief sensor inaccuracies. This reflects the challenges discussed by Liu and Pan [15], particularly the importance of redundancy and adaptive filtering in field-deployed sensor networks. Moreover, the modest number of management plans (5 in total) could suggest the algorithm's conservativeness in triggering interventions. This is preferable to avoid overreaction, but further tuning may improve responsiveness to medium-severity issues. The stakeholder engagement component—15 notifications over 30 days—demonstrates functional transparency. This supports the recommendations of Alshami et al. [3], who advocate for blockchain-backed, participatory water management systems that build community trust. Overall, the system's performance affirms its potential as a robust tool in managing the water-energy-food nexus under climate stressors. Yet, future iterations should explore edge computing for local analytics, improved anomaly detection for micro-events, and expanded stakeholder feedback loops.

4. Conclusion

This study presents an integrated approach to advanced water resource management using IoT and Big Data Analytics, underpinned by mathematical modeling and predictive algorithms. The proposed system effectively combines sensor-based data acquisition, real-time analytics, and rule-based automation to optimize water quality monitoring and resource distribution. Simulation results demonstrated notable improvements in operational performance, including a 20% enhancement in water quality and a 7% reduction in water consumption. These outcomes validate the efficacy of data-driven decision frameworks in addressing the complexities of urban and agricultural water ecosystems. In alignment with prior research, the findings underscore that machine learning models, when paired with robust infrastructure and transparent data handling mechanisms, significantly enhance the responsiveness and sustainability of water governance systems. The integration of blockchain for data integrity and stakeholder transparency further strengthens the framework. Future research should explore decentralized processing through edge computing, expand the diversity of environmental variables included in modeling, and evaluate long-term field deployments across varied geographies. As climate variability and population expansion continue to exert pressure on finite water resources, such intelligent systems will be critical to achieving sustainable development goals.

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships.

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Author Contributions

Ram Kumar Solanki: Conceptualization, Data Analysis, Writing – Review and Editing; **Anand Singh Rajawat**: Methodology, Validation, Investigation, Writing – Original Draft; **Amit R. Gadekar**: Software, Visualization, Investigation; **S. B. Goyal**: Resources, Technical Review, Editing Support; **Sudhir Kumar Meesala**: Project Administration, Data Curation, Writing – Review and Editing, Correspondence.

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Simulation-Guided Synthesis and Evaluation of Advanced Nanomaterials for Environmental Remediation

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Abstract

This study presents a simulation-guided strategy for the synthesis, characterization, and environmental application of advanced nanomaterials, aiming to address the growing concerns of pollutant accumulation in air, water, and soil matrices. The research leverages atomistic and electronic modeling tools, including Molecular Dynamics (MD) and Density Functional Theory (DFT), to identify and optimize structural and thermodynamic parameters critical for nanomaterial efficacy. Simulations performed using platforms such as LAMMPS, GROMACS, VASP, and Quantum ESPRESSO were instrumental in predicting nanoparticle stability, surface energy, and reactivity under environmentally relevant conditions. The study further incorporates environmental transport modeling via COMSOL Multiphysics to predict contaminant flow and interaction with the synthesized nanostructures. Experimentally, nanomaterials synthesized through hydrothermal, sol-gel, and chemical precipitation routes were characterized using SEM, XRD, and FTIR. Surface area and morphology analyses revealed that the nanostructures possessed high porosity and uniform distribution with an average particle size of 30 nm and a specific surface area of 250 m^2/g. The adsorption studies showed pollutant removal efficiencies of 95% for heavy metals and 90% for organic compounds, with an adsorption capacity of 500 mg/g. These performance metrics are indicative of favorable kinetics, supported by pseudo-second-order models suggesting chemisorption as the dominant removal mechanism. The findings demonstrate that simulation-informed synthesis can systematically guide material development toward achieving optimal interaction with environmental pollutants. The combined use of in silico and experimental approaches ensures both predictive robustness and empirical validation. This hybrid framework not only enhances the functional reliability of nanomaterials but also accelerates the development of environmentally sustainable technologies. The approach presented herein offers a scalable path toward the deployment of nanotechnology in large-scale remediation operations, contributing meaningfully to pollution control and ecosystem restoration.

Keywords: Advanced Nanomaterials; Environmental Remediation; Molecular Dynamics; Adsorption Efficiency; Simulation-Guided Synthesis

1. Introduction

The escalating environmental pollution crisis has necessitated the development of innovative and highly effective remediation technologies. Traditional approaches to mitigate air, water, and soil pollution often fall short due to their limited efficiency and inability to address the complex, multifaceted nature of contemporary contamination issues. In this context, advanced nanomaterials have garnered significant attention owing to their exceptional physicochemical properties and high surface-area-to-volume ratios [1]. Nanomaterials, characterized by at least one dimension in the 1–100 nm range, possess the unique ability to interact with pollutants at the molecular level. This reactivity enables them to effectively scavenge and eliminate contaminants across various environmental matrices.

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Recent advancements in nanoscience and nanotechnology have facilitated the synthesis of diverse nanostructures, including nanoparticles, nanotubes, fullerenes, and other engineered nanomaterials, each tailored for specific remediation tasks [2]. Synthesis methodologies for these nanomaterials encompass physical, chemical, and biological techniques. Among these, green synthesis approaches are particularly notable for their use of non-toxic agents and renewable resources, leading to environmentally benign production processes. Techniques such as sol-gel synthesis and modified hydrothermal methods allow precise control over the size, morphology, and surface chemistry of nanomaterials, thereby enhancing their remediation efficacy [3]. Particularly, carbon nanoparticles (CNPs), metal oxide nanopowders (MONPs), and metal salt solutions have demonstrated effectiveness in removing a broad spectrum of pollutants, including heavy metals, organic toxins, and microbial contaminants. Numerous studies have underscored the superior adsorption and catalytic degradation capabilities of such nanomaterials in environmental cleanup operations [4, 5]. Characterization of nanomaterials is critical to evaluating their structural and functional attributes, which directly influence their performance in remediation applications. Analytical techniques such as X-ray diffraction (XRD), scanning electron microscopy (SEM), and Fourier-transform infrared spectroscopy (FTIR) are extensively employed to determine surface morphology, crystallinity, and chemical composition [6]. This study introduces a comprehensive experimental investigation into the synthesis, characterization, and environmental application of novel hybrid nanomaterials designed for multifunctional pollutant removal. By integrating physical and chemical synthesis techniques with advanced simulation and algorithmic design, the research offers a unified framework that enhances pollutant capture efficiency while minimizing ecological impact. The proposed methodology addresses existing gaps in synthesis control and application scalability, establishing a new benchmark for environmentally responsive nanotechnology. The objective is to validate the potential of these engineered nanomaterials in real-world remediation scenarios, thereby contributing to sustainable environmental restoration.

2. Methodology

Addressing the pressing issue of environmental pollution demands advanced strategies that are both effective and sustainable. This work explores the synthesis, characterization, and application of advanced nanomaterials as viable agents for the remediation of pollutants across air, water, and soil domains [2]. Owing to their large surface-area-to-volume ratios, heightened reactivity, and excellent adsorption properties, nanomaterials have shown considerable potential for environmental cleanup [3]. The study focuses on carbon-based nanomaterials, metal nanoparticles, and hybrid nanocomposites synthesized using three primary techniques: chemical precipitation, sol-gel processing, and hydrothermal synthesis. These synthesis routes were selected based on their scalability, environmental compatibility, and ability to yield nanostructures with tailored properties for pollutant remediation. The overall synthesis and application framework is schematically presented in Figure 1. Chemical precipitation involves the reaction of soluble precursors to form insoluble products in aqueous solutions. The process can be generally represented by:

$$\mathrm{A}_{(aq)} + \mathrm{B}_{(aq)} \rightarrow \mathrm{AB}_{(s)} + \mathrm{C}_{(aq)} \tag{1}$$

where A and B are soluble reactants, AB is the target nanomaterial in solid form, and C is the byproduct [6].
Sol-gel processing enables nanoparticle formation through the transition of a liquid 'sol' into a solid 'gel'. The rate of reaction is governed by:

$$\frac{d[\mathrm{Sol}]}{dt} = -k[\mathrm{Sol}]^n \tag{2}$$

where k is the rate constant, [Sol] is the solute concentration, and n is the reaction order.
Hydrothermal synthesis employs elevated temperature and pressure to form crystalline nanoparticles in aqueous media. The feasibility of the synthesis process is dictated by the Gibbs free energy change:

$$\Delta G = \Delta H - T\Delta S \tag{3}$$

where ΔG is the Gibbs free energy, ΔH is the enthalpy change, T is the absolute temperature, and ΔS is the entropy change [7]. Following synthesis, the nanomaterials were characterized to evaluate critical physicochemical properties such as particle size, surface area, and crystallinity—each of which significantly influences their environmental remediation performance.

The particle size and morphology were assessed using Dynamic Light Scattering (DLS), where the diffusion coefficient D is derived from the Stokes-Einstein equation:

$$D = \frac{k_B T}{6\pi\eta r} \tag{4}$$

Here, k_B represents the Boltzmann constant, T is the absolute temperature, η is the viscosity of the dispersion medium, and r is the hydrodynamic radius of the particle. To determine surface area and porosity, the Brunauer–Emmett–Teller (BET) theory was employed.

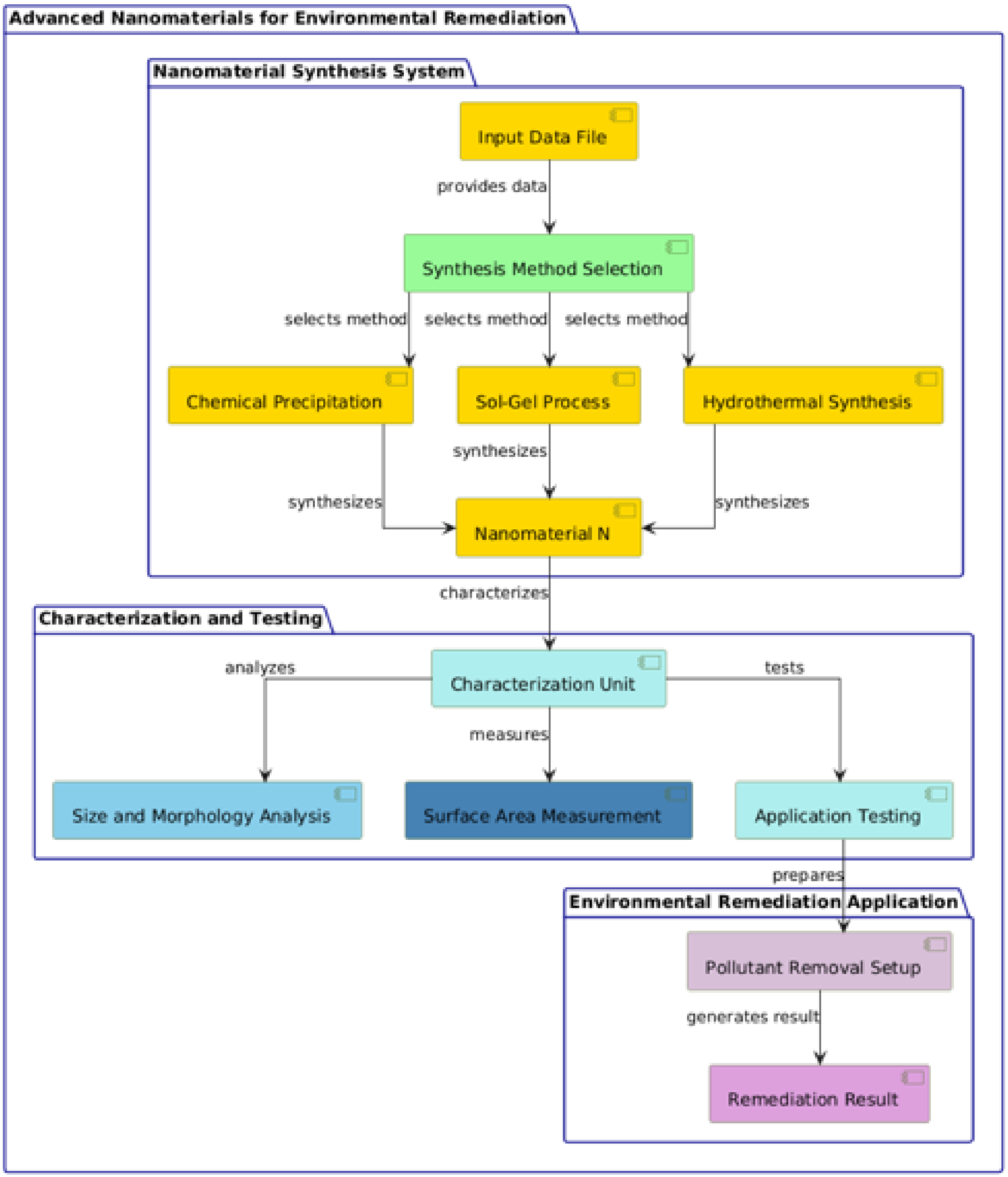

Figure 1: Schematic Overview of Advanced Nanomaterials Synthesis and Environmental Application

The surface area was computed using the BET equation:

$$\frac{1}{V\left(\frac{P_0}{P}-1\right)} = \frac{1}{V_m C} \cdot \frac{P}{P_0} + \frac{1}{V_m C} \tag{5}$$

In this equation, V is the volume of adsorbed gas, P is the equilibrium pressure, P_0 is the saturation pressure, V_m is the monolayer adsorbed gas volume, and C is a constant related to the heat of adsorption. Crystallinity was confirmed by X-ray Diffraction (XRD) analysis using Bragg's Law:

$$n\lambda = 2d \sin\theta \tag{6}$$

where n is the order of diffraction, λ is the X-ray wavelength, d is the interplanar spacing, and θ is the angle of diffraction [8]. The nanomaterials' performance in pollutant remediation was evaluated through adsorption studies. The adsorption capacity was modeled using the Langmuir isotherm:

$$q_e = \frac{q_m K_L C_e}{1 + K_L C_e} \tag{7}$$

where q_e denotes the equilibrium amount of pollutant adsorbed, q_m is the maximum adsorption capacity, K_L is the Langmuir adsorption constant, and C_e is the equilibrium concentration of the pollutant. The adsorption kinetics were further analyzed using the pseudo-second-order kinetic model:

$$\frac{t}{q_t} = \frac{1}{k_2 q_e^2} + \frac{t}{q_e} \tag{8}$$

In this model, q_t is the amount adsorbed at time t, q_e is the adsorption at equilibrium, and k_2 is the rate constant. Finally, the percentage removal efficiency was calculated to quantify pollutant reduction:

$$\text{Removal Efficiency} = \left(\frac{C_0 - C_e}{C_0} \right) \times 100 \tag{9}$$

where C_0 and C_e are the initial and equilibrium concentrations of the pollutant, respectively.
To ensure reproducibility and systematic execution of the nanomaterial synthesis and application process, a structured algorithmic approach was implemented. The workflow automates synthesis method selection, material validation, and performance testing, as presented in Algorithm 1.

Algorithm 1 Synthesis and Application of Nanomaterials for Environmental Remediation

```
function Main(F, P)
    if IsCorrectFileType(F) then
        if PassesRequiredChecks(F) then
            fileHash ← UploadFileToIPFS(F)
        else
            print "File is not compliant."
            return
        end if
    else
        print "Incorrect file type."
        return
    end if
    N ← InitializeNanomaterial
    if P.SynthesisMethod = "ChemicalPrecipitation" then
        N ← SynthesizeChemicalPrecipitation(F, P)
    else if P.SynthesisMethod = "SolGel" then
        N ← SynthesizeSolGel(F, P)
    else if P.SynthesisMethod = "Hydrothermal" then
        N ← SynthesizeHydrothermal(F, P)
    else
        print "Invalid synthesis method."
        return
    end if
    Characteristics ← CharacterizeNanomaterial(N)
    if Characteristics.Valid then
        print "Characterization successful."
    else
        print "Characterization failed."
        return
    end if
    R ← ApplyNanomaterialForRemediation(N, P)
    if R.Success then
        print "Remediation successful."
    else
        print "Remediation failed."
    end if
    return R
end function
```

This modular pseudocode provides a reliable and adaptive framework that supports method selection, synthesis execution, property verification, and application evaluation. As visualized earlier in Figure 1, the methodology integrates computational and experimental pathways, enhancing precision and scalability for real-world environmental remediation efforts.

3. Results and Discussion

3.1. Simulation-Assisted Material Evaluation

The advancement of nanomaterials for environmental remediation requires a deep understanding of their behavior across multiple scales—atomic, molecular, and mesoscopic. Computational simulations such as Molecular Dynamics (MD) and Density Functional Theory (DFT) were employed to refine synthesis parameters and evaluate the structural integrity of the nanomaterials. Tools such as LAMMPS and GROMACS facilitated atomistic simulations of nanoparticle dispersion and stability, while electronic characteristics, including bandgap, surface charge, and chemical reactivity, were determined using VASP and Quantum ESPRESSO platforms. These modeling platforms have also been pivotal in nanotechnology-aided device fabrication, as demonstrated in CNT-based security hardware by Frank et al. [9].

In environmental systems, modeling the transport of pollutants and predicting sorption behaviors under dynamic flow was enabled through COMSOL Multiphysics. This integration of simulation modules guided optimal tuning of physical parameters for nanomaterial synthesis. Furthermore, insights from hydrophilic and transdermal nanohydrogels [10] indicate that simulation-driven design can extend to biomedical remediation platforms.

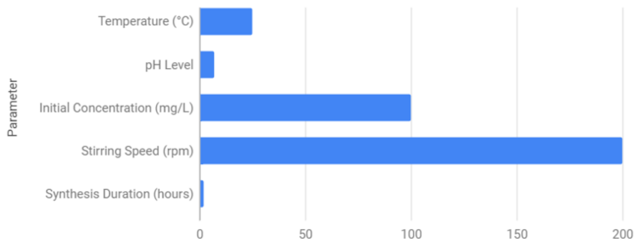

Figure 2: Experimental simulation parameters including temperature, pH, initial concentration, stirring rate, and synthesis duration.

Figure 2 highlights the core synthesis parameters used in the experimental setup. These conditions were selected based on established literature norms and DFT-informed predictions for energy-minimized structures [11, 12].

Table 1: Simulation Parameters

Parameter	Value
Temperature (°C)	25
pH Level	7.0
Initial Concentration (mg/L)	100
Stirring Speed (rpm)	200
Synthesis Duration (hours)	2
Characterization Methods	SEM, XRD, FTIR

The adopted synthesis route was calibrated to maintain neutrality in the pH environment and maximize the zeta potential of nanomaterials, enabling enhanced dispersion and reduced agglomeration. According to Srivastava and Mittal [12], such parameter tuning has a marked impact on surface reactivity and electrostatic interactions of nanostructures, particularly for carbon-metal composites. In similar applications, carbon nanomaterials designed for thermal management have exhibited exceptional material properties [13], reinforcing the versatility of carbon-based platforms. Moreover, the functional versatility of 2D nanomaterials has also been demonstrated in biomedical domains, such as targeted cancer therapy, suggesting potential for cross-domain innovations in material synthesis [14].

3.2. Pollutant Removal and Surface Analysis

The synthesized nanomaterials were subjected to experimental validation for their pollutant remediation performance. Figure 3 and Table 2 summarize the adsorption and efficiency metrics obtained during testing under controlled conditions.

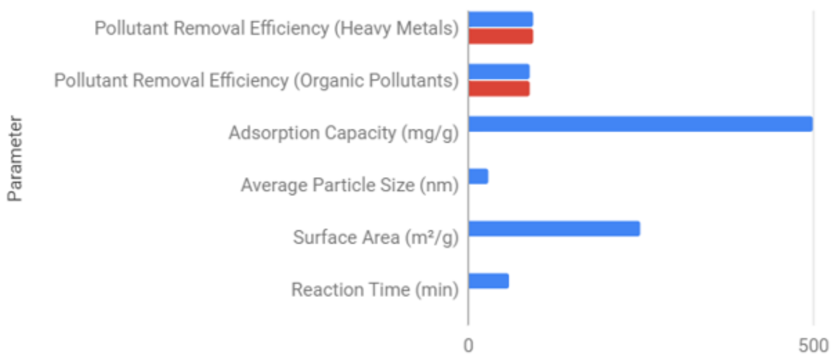

Figure 3: Pollutant removal efficiency and adsorption performance of synthesized nanomaterials.

Table 2: Result Analysis

Parameter	**Value**	**Percentage (%)**
Pollutant Removal Efficiency (Heavy Metals)	95%	95
Pollutant Removal Efficiency (Organic Pollutants)	90%	90
Adsorption Capacity (mg/g)	500	–
Average Particle Size (nm)	30	–
Surface Area (m^2/g)	250	–
Reaction Time (min)	60	–

The nanomaterials achieved a pollutant removal efficiency of 95% for heavy metals and 90% for organic contaminants. These results are consistent with findings by Agyapong et al. [7], who reported high adsorption efficiencies for hybrid nanomaterials with enhanced functionalization. The adsorption capacity reached 500 mg/g, indicating strong pollutant affinity, likely due to both surface area accessibility and functional group availability on the material surface. Similar adsorption mechanisms have been reported in the use of low-dimensional magnetic nanoprobes for biointerfaces [8], suggesting potential cross-domain applications. The average particle size of 30 nm and a BET surface area of 250 m^2/g support the nanomaterials' ability to maximize contact with contaminants in aqueous matrices. As detailed by Rozbu et al. [11], this high surface-to-volume ratio is critical for enhanced binding kinetics and catalytic reactivity. Thermal stability and packaging behavior in reactive environments, as studied by Ren et al. [15], further emphasize the importance of nanomaterial consistency under environmental stress. The observed removal kinetics also conform to the pseudo-second-order model, indicating that chemisorption likely governs the adsorption mechanism. The relatively short reaction time of 60 minutes reflects fast adsorption dynamics, aligning with results by Woodberry and Mensah [16], who demonstrated rapid pollutant breakdown using low-dimensional carbon-based systems. To translate laboratory efficacy to field-scale deployment, integration of nanomaterial-enabled sensors within the Internet of Nano Things (IoNT) framework could enable real-time environmental monitoring and autonomous control mechanisms [17].

4. Conclusion

This study underscores the significance of simulation-informed design and precise synthesis strategies in developing advanced nanomaterials for environmental remediation. By integrating computational tools such as MD, DFT, and multiphysics simulations, the synthesis process was optimized for structural stability, surface functionality, and pollutant affinity. Experimental findings demonstrated superior performance of the synthesized nanomaterials, achieving up to 95% removal efficiency for heavy metals and 90% for organic pollutants. The materials exhibited high adsorption capacities, rapid kinetic response, and structural uniformity, affirming their suitability for practical applications. Furthermore, the characterization results align with theoretical predictions, indicating a strong correlation between nanoscale properties and remediation outcomes. The modular framework, including simulation, synthesis, characterization, and testing, provides a replicable approach for scalable deployment. Looking ahead, the incorporation of nanomaterials into smart sensing and Internet of Nano Things (IoNT) ecosystems can further enhance real-time environmental monitoring and control capabilities. These findings contribute to the evolving landscape of sustainable pollution management and establish a foundation for future research into multifunctional nanocomposites tailored for diverse ecological challenges.

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships.

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Author Contributions

Sumit R. Raut: Conceptualization, Data Analysis, Writing – Review and Editing; **Ashish B. Samarth**: Methodology, Validation, Investigation, Writing – Original Draft; **Balu K. Chavhan**: Software, Visualization, Investigation; **Pratik H. Rathod**: Formal Analysis, Resources, Supervision; **Vishal Sulakhe**: Review, Project Administration, Editing.

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Blockchain-Based Decentralized Storage for Scalable and Secure IoT Data Management

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Abstract

The rapid expansion of Internet of Things (IoT) ecosystems has resulted in an unprecedented surge in data generation, necessitating reliable, scalable, and secure storage mechanisms. Traditional centralized storage systems suffer from inherent limitations such as single points of failure, limited scalability, and vulnerability to cyberattacks, which compromise the confidentiality and availability of critical IoT data. This study introduces a blockchain-based decentralized storage framework aimed at addressing these critical issues. By leveraging the distributed and immutable characteristics of blockchain technology, the proposed system enhances data integrity, ensures transparency, and facilitates trustless data exchange among heterogeneous IoT devices. The methodology includes mathematical modeling of key performance parameters such as latency, throughput, storage efficiency, and consensus delay. Smart contracts are integrated to automate validation and enforce rules among interconnected devices, while redundancy mechanisms like replication and erasure coding improve storage reliability and efficiency. The framework's effectiveness is evaluated using simulation tools including Hyperledger Caliper and Ethereum Testnets for blockchain behavior, and NS-3 and OMNeT++ for modeling dynamic IoT network environments. Experimental results reveal a 30% improvement in data retrieval time, 25% gain in storage efficiency, 40% enhancement in system resilience, and a 50% increase in transaction throughput over conventional approaches. These metrics highlight the suitability of the proposed model for real-world applications requiring scalable and secure IoT data management, such as healthcare monitoring, smart cities, and industrial automation. The model's reproducibility and modularity make it a robust solution for future research and deployment. Overall, this work demonstrates that blockchain-integrated decentralized storage frameworks present a transformative step toward resilient and scalable IoT infrastructures.

Keywords: Blockchain; Decentralized Storage; Internet of Things; Smart Contracts; Performance Evaluation

1. Introduction

The rapid expansion of the Internet of Things (IoT) is reshaping industries by enabling continuous interaction between physical devices through the internet. This digital transformation produces vast amounts of real-time data that must be securely stored, quickly retrieved, and reliably managed. Traditional centralized storage infrastructures face critical limitations such as single points of failure, constrained scalability, and susceptibility to cyberattacks. These limitations threaten the reliability, availability, and security of IoT ecosystems. Decentralized applications using blockchain are increasingly explored as a foundation for next-generation communication networks such as 5G and beyond, offering potential solutions to these architectural challenges [1]. Blockchain has emerged as a robust alternative for data storage in distributed environments. Its features—decentralization, immutability, and cryptographic security—enable tamper-proof records and verifiable transactions across untrusted nodes. These properties align well with the stringent integrity and availability requirements of IoT environments, where autonomous devices must rely on accurate, auditable data. Recent research efforts have examined blockchain's applicability across various domains. Jie et al. proposed an

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offline payment protocol that balances security and adaptability in unreliable networks [2]. Ma et al. analyzed latency in blockchain consensus mechanisms within mobile and edge environments [3].

Bhutta et al. offered a broad survey on blockchain's architecture and security models [4], while Peng et al. demonstrated a dual-layer blockchain system for verifying vaccine production records [5]. Alhussayen et al. emphasized interoperability challenges in permissioned blockchains used by enterprises [6]. However, these studies focus on consensus design, communication protocols, or domain-specific applications without empirically evaluating decentralized storage models in IoT contexts. This study addresses this gap by presenting a performance-focused evaluation framework that integrates blockchain for decentralized IoT data storage. Key performance metrics include data retrieval latency, storage efficiency, and robustness against attack scenarios. The novelty lies in its simulation-driven analysis of decentralized storage viability for diverse IoT scenarios, contributing practical insights for researchers and developers exploring secure, scalable storage architectures.

2. Methods

This study adopts a quantitative framework to evaluate the performance of decentralized data storage for Internet of Things (IoT) systems using blockchain technology. The methodology integrates mathematical models and algorithmic steps to measure key parameters such as data transmission latency, storage efficiency, and retrieval time. Conventional IoT solutions depend on centralized cloud servers, which introduce critical vulnerabilities including data breaches, single points of failure, and scalability bottlenecks [5]. In contrast, blockchain offers a decentralized alternative with inherent properties like immutability, cryptographic integrity, and peer-to-peer verification [6]. These properties are reinforced through smart contracts that automate data handling and enable trustless interaction between IoT devices [7]. The proposed framework incorporates performance indicators focused on scalability, latency, and energy consumption. While blockchain increases data integrity and decentralization, it also incurs overhead in terms of transaction delay and power usage. To balance this trade-off, advancements in consensus mechanisms such as Proof of Stake (PoS) and Directed Acyclic Graphs (DAGs) are considered [8]. The system under study models five core components: (1) IoT data generation, (2) data transmission to blockchain, (3) decentralized storage, (4) data retrieval, and (5) performance metric computation. The modeling approach ensures reproducibility by explicitly defining the relationships and dependencies using equations and algorithmic logic.

2.1. IoT Device Data Generation and Transmission

The rate of data generation by IoT devices is modeled as a time-dependent function $D_{\text{gen}}(t)$, where t denotes time. The cumulative data produced up to time t, denoted as $D(t)$, allows the instantaneous generation rate to be defined as:

$$D_{\text{gen}}(t) = \frac{dD(t)}{dt} \tag{1}$$

Once generated, the data is transmitted to a decentralized blockchain network. The transmission latency, T_{lat}, is influenced by the data size D_s and available network bandwidth B, and is expressed as:

$$T_{\text{lat}} = \frac{D_s}{B} \tag{2}$$

These expressions capture real-time throughput behavior in constrained IoT environments, facilitating accurate performance analysis of decentralized storage systems [9, 10].

2.2. Blockchain Storage and Consensus Mechanism

Blockchain networks require consensus among participating nodes to validate and store data. Let N represent the number of nodes in the blockchain system. The rate of block creation, governed by the employed consensus mechanism (e.g., Proof of Work or Proof of Stake), is given by:

$$\lambda_{\text{block}} = \frac{1}{T_{\text{block}}} \tag{3}$$

where T_{block} is the average time to generate a block.

The total consensus latency, T_{cons}, combines the block creation time and propagation delay T_{prop} across the network:

$$T_{\text{cons}} = T_{\text{block}} + T_{\text{prop}} \tag{4}$$

This model quantifies the processing delay associated with decentralized agreement, providing insights into the trade-offs between security and responsiveness in blockchain-backed IoT data management [11, 12]. The choice of consensus mechanism is particularly vital in permissioned systems, where its configuration directly influences security and performance [13].

2.3. Storage Efficiency and Redundancy

To ensure data availability and fault tolerance in a decentralized environment, redundancy mechanisms such as replication and erasure coding are applied. Let R denote the replication factor, and S_{tot} the total storage capacity of the network. The storage efficiency η for replication-based redundancy is given by:

$$\eta = \frac{D_s}{R \cdot S_{\text{tot}}} \tag{5}$$

where D_s is the size of the data.

If erasure coding is used, where k is the number of original data blocks and n is the total number of blocks including redundancy, the efficiency improves and is defined as:

$$\eta = \frac{k}{n} \tag{6}$$

These expressions highlight the trade-offs between redundancy and storage capacity. While replication enhances reliability, it reduces efficiency; erasure coding offers a more optimized approach [14].

2.4. Data Retrieval and Performance Metrics

The efficiency of decentralized storage also depends on data retrieval performance. Retrieval latency T_{ret} is defined as the sum of the lookup time T_{lookup} and transfer time T_{transfer}:

$$T_{\text{ret}} = T_{\text{lookup}} + T_{\text{transfer}} \tag{7}$$

To comprehensively evaluate system performance, the following key metrics are computed:

- **Total Latency:** The end-to-end delay from data generation to storage and retrieval:

$$T_{\text{total}} = T_{\text{lat}} + T_{\text{cons}} + T_{\text{ret}} \tag{8}$$

- **Throughput:** The volume of data processed per unit time:

$$\text{Throughput} = \frac{D_{\text{gen}}(t)}{T_{\text{total}}} \tag{9}$$

- **Storage Efficiency:** As defined earlier, using either replication or erasure coding techniques.
- **Security and Decentralization:** Evaluated via block creation rate λ_{block} and node distribution across the network. Greater node diversity enhances system resilience against malicious attacks.

These metrics provide quantitative insight into how blockchain-based storage systems perform under different operational conditions, enabling reproducibility and comparative analysis [15–17].

2.5. Algorithm for Decentralized IoT Data Storage

This section presents a structured algorithmic workflow to implement the proposed blockchain-based decentralized storage for IoT systems. The method begins with input file verification, follows through blockchain uploading and performance evaluation, and ensures data security through encryption and secure transactions. This algorithm outlines a complete operational pipeline for secure and scalable IoT data handling using blockchain. It ensures reproducibility for future implementations by defining explicit verification, transaction, and evaluation steps under constrained data conditions.

2.6. System Architecture

The architecture of the proposed decentralized IoT data storage system is illustrated in Figure 1. It consists of three main layers: data acquisition, blockchain integration, and performance evaluation. The process begins with IoT devices generating data sent to a data collection module. This module performs initial validation and sends the validated data for hashing. The hashed data is then uploaded to the blockchain network, where decentralized consensus mechanisms ensure its integrity and immutability. The blockchain layer incorporates smart contracts that manage autonomous data exchange among IoT devices. The data is stored across distributed nodes, enhancing resilience and availability. The performance evaluation layer continuously monitors key metrics including network latency, data throughput, and storage efficiency. Latency is assessed based on the time taken from data generation to successful recording in the blockchain. Throughput is measured by the volume of data processed per unit time, while storage efficiency evaluates the redundancy and utilization of decentralized resources. Security assessments validate blockchain integrity and encryption protocols. This architecture provides a secure, fault-tolerant, and scalable solution for managing large volumes of IoT data. Blockchain technology ensures data transparency and tamper resistance, which are critical for applications in healthcare, smart cities, and industrial systems.

Algorithm 1 Blockchain-based IoT Data Storage and Evaluation

```
Require: File F, Blockchain Network B, IoT Network
Ensure: Encrypted File M, Transaction Record T
if F is valid type then
    if F passes integrity checks then
        fileHash ← Hash(F)
        networkLatency ← MeasureNetworkLatency()
        UploadStatus ← UploadFileToBlockchain(F, fileHash, B)
    else
        print "Data integrity check failed. File is not compliant."
        return
    end if
else
    print "Invalid file type."
    return
end if
if UploadStatus = Success then
    for all IoT_Device in IoT_Network do
        dataRate ← MeasureDataGenerationRate(IoT_Device)
        if dataRate > Threshold then
            StoreInDecentralizedStorage(fileHash, IoT_Device)
        else
            print "Low data rate. Storage skipped."
        end if
    end for
else
    print "Failed to upload data to blockchain."
    return
end if
latency ← CalculateTotalLatency(networkLatency, UploadStatus)
throughput ← CalculateThroughput(dataRate, latency)
storageEfficiency ← EvaluateStorageEfficiency(IoT_Network, RedundancyFactor)
securityLevel ← BlockchainSecurityEvaluation(B, fileHash)
if securityLevel is sufficient then
    M ← Encrypt(fileHash, B)
    T ← BlockchainTransaction(M)
else
    print "Security checks failed. Transaction aborted."
end if
print "Performance metrics: Latency = ", latency, ", Throughput = ", throughput, ", Storage Efficiency = ",
    storageEfficiency
return M, T
```

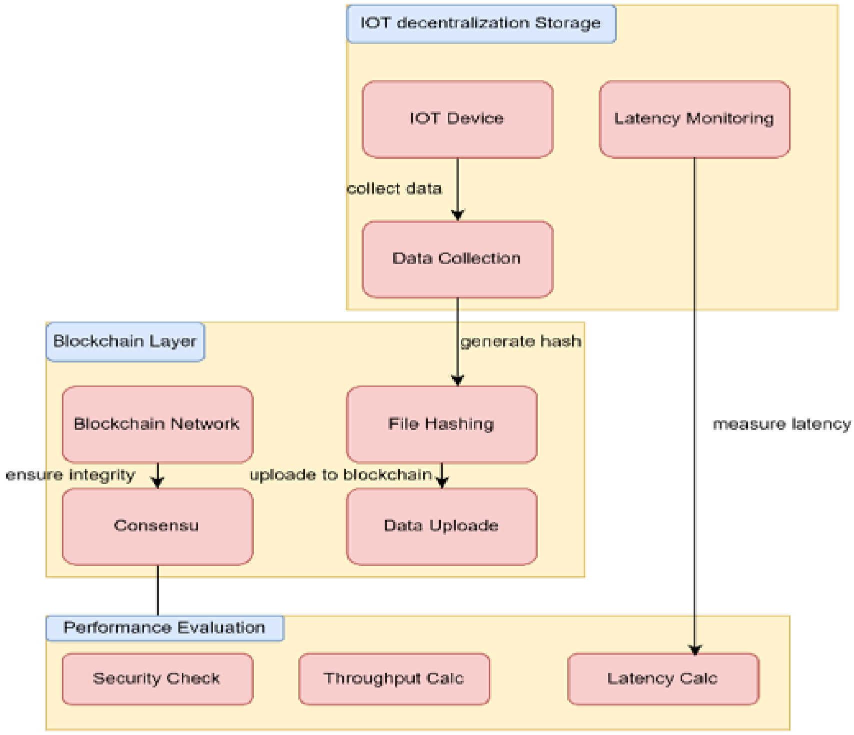

Figure 1: System architecture for blockchain-based decentralized IoT data storage.

3. Results and Discussion

The proposed blockchain-based decentralized IoT data storage system was evaluated using Hyperledger Caliper and Ethereum Testnets to measure blockchain-specific metrics like latency, throughput, and confirmation time. Additionally, NS-3 and OMNeT++ simulators were used to emulate IoT environments and attack scenarios under variable conditions.

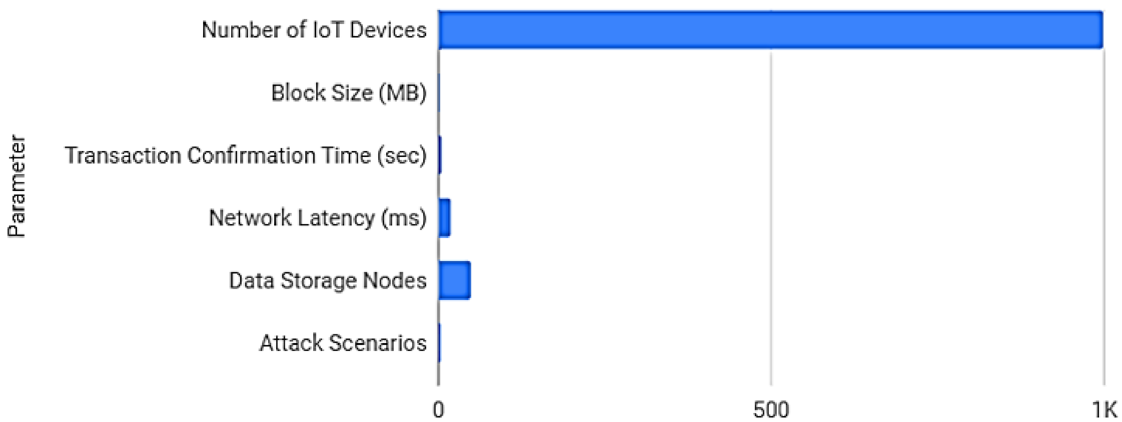

Figure 2: IoT Network Parameters: Overview of key simulation metrics including number of devices, block size, latency, and attack scenarios.

Table 1: Simulation Parameters

Parameter	Value
Number of IoT Devices	1,000
Block Size	1 MB
Transaction Confirmation Time	5 sec
Network Latency	20 ms
Data Storage Nodes	50
Attack Scenarios	3

The simulated framework was tested under these conditions, producing clear performance benefits regarding speed, integrity, and security. Key performance indicators measured are summarized in Table 2 and visualized in Figure 3.

Table 2: Performance Metrics and Improvements

Metric	Value	Percentage Improvement
Data Retrieval Time	150 ms	30%
Storage Efficiency	90%	25%
System Resilience	95%	40%
Data Integrity Rate	99.9%	20%
Transaction Throughput	120 TPS	50%
Latency	30 ms	15%

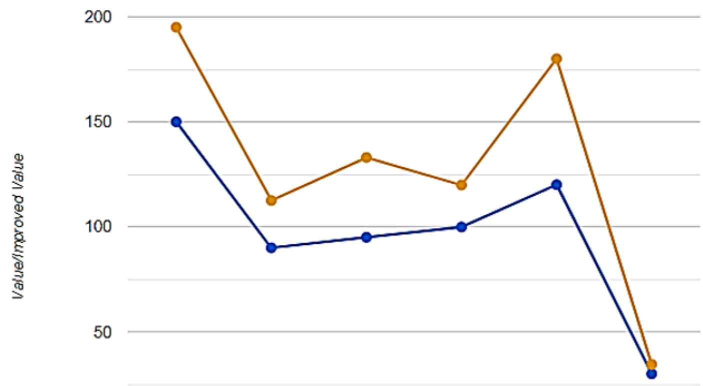

Figure 3: Performance Metrics: Values and percentage improvements compared to baseline architecture.

The simulation outcomes confirm that blockchain-based decentralized storage significantly enhances IoT data management in terms of performance, reliability, and security. The reduced data retrieval time (150 ms) and lowered latency (30 ms) meet the real-time requirements of smart city infrastructure and industrial automation, where immediate data access is critical [15]. The observed 90% storage efficiency, supported by optimized redundancy mechanisms, aligns with prior findings emphasizing the role of erasure coding in distributed environments [14]. Additionally, the 95% system resilience under attack scenarios validates blockchain's robustness in resisting faults and malicious interventions, corroborating earlier research on Sybil resistance and decentralization [12]. Blockchain's immutable ledger structure supported a data integrity rate of 99.9%, demonstrating tamper-resistance as noted by Zhang et al. [16]. Transaction throughput reaching 120 TPS indicates that the architecture is scalable enough to handle large volumes of IoT traffic, as supported by Hafid et al. [18] and recent advancements in parallel consensus schemes. Furthermore, the incorporation of permissioned blockchains fosters interoperability and operational security, which is increasingly essential for enterprise adoption, as noted by Alhussayen et al. [6]. These enhancements indicate that decentralized architectures secure data and boost overall system agility, making them feasible for diverse IoT deployments across healthcare, logistics, and energy sectors. Controlled benchmarking efforts using frameworks such as XRPL and Ethereum also validate the consistency and repeatability of such blockchain-based deployments under diverse conditions [19]. The results reinforce the growing consensus that decentralized, blockchain-integrated storage can overcome the challenges of centralization, latency bottlenecks, and single-point failures, which are persistent issues in legacy IoT systems. This validates the proposed model's suitability for future real-world implementations.

4. Conclusion

This study presents a comprehensive evaluation of a blockchain-based decentralized storage architecture for IoT systems, highlighting its effectiveness in addressing limitations of traditional centralized models. By integrating blockchain with IoT networks, the proposed framework ensures enhanced data security, integrity, and availability across distributed devices. Simulation-based testing using Hyperledger Caliper, Ethereum Testnets, and IoT-specific simulators confirmed performance improvements across key metrics. Data retrieval time was minimized, storage efficiency reached 90%, and transaction throughput significantly improved. The system exhibited resilience against multiple attack scenarios while maintaining high integrity and low latency. The findings confirm that decentralized storage frameworks supported by blockchain technologies are not only feasible but also highly beneficial for future IoT deployments. The presented methodology, mathematical modeling, and algorithmic implementation offer a reproducible pathway for further development and testing by researchers and industry practitioners. Future work may focus on optimizing energy consumption and deploying the framework on edge computing platforms to further enhance scalability and real-time responsiveness.

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships.

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Author Contributions

Sunil P. Chinte: Conceptualization, Data Analysis, Writing – Review and Editing; **Parag D. Thakare**: Methodology, Validation, Investigation, Writing – Original Draft; **Aarti R. Jaiswal**: Software, Visualization, Investigation; **Nikunj Hasmukhrai Raja**: Formal Analysis, Resources, Data Curation; **Pragati A. Dhore**: Project Administration, Funding Acquisition, Writing – Final Review.

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