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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.

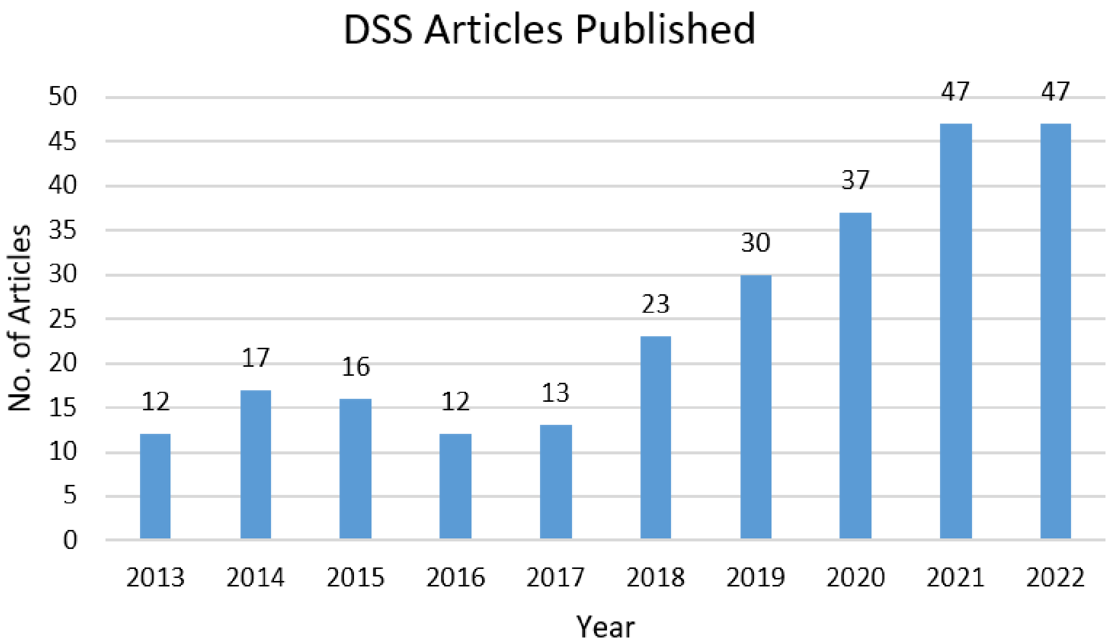

Figure 1: Statistics of DSS-related articles published in IEEE journals (2013–2022)

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.

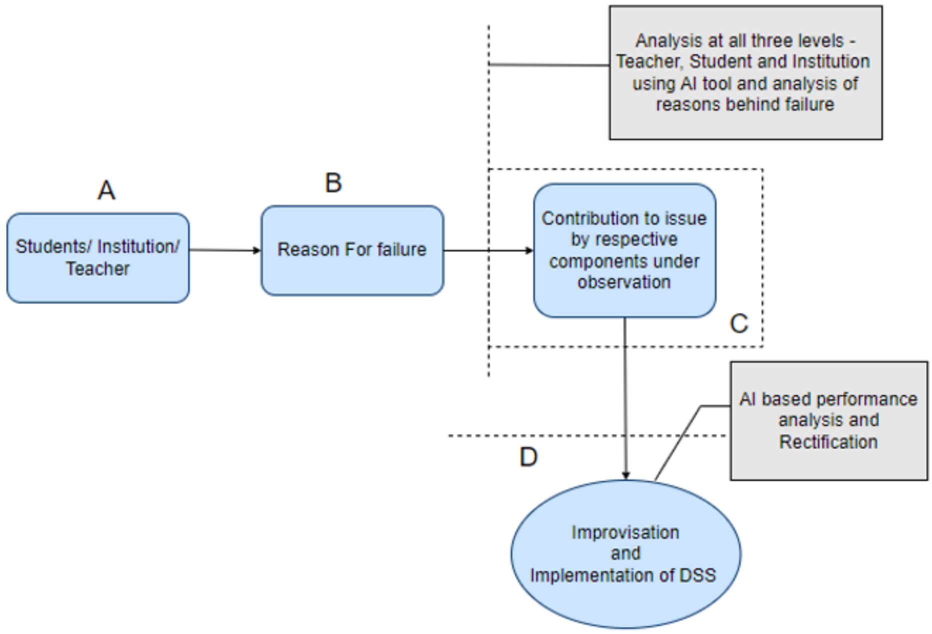

Figure 2: Proposed 4-level DSS model

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.

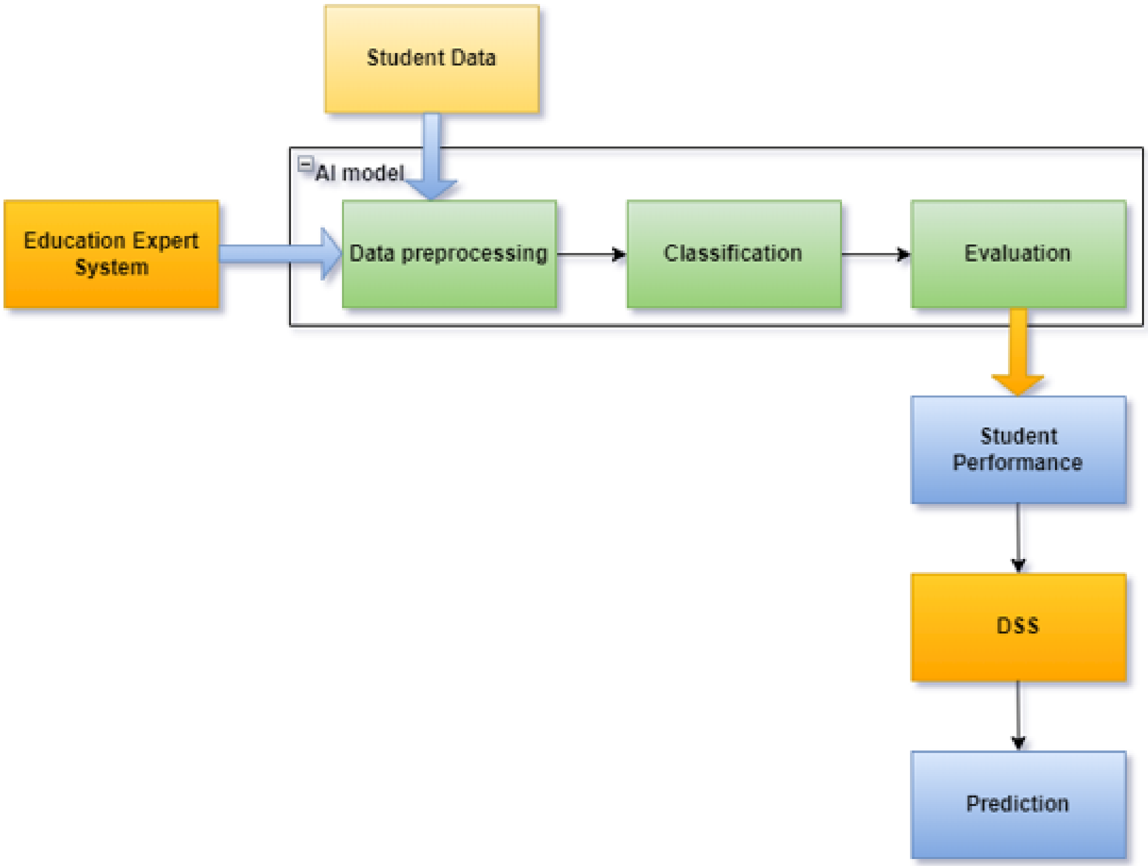

Figure 3: Block diagram of data processing and prediction in DSS

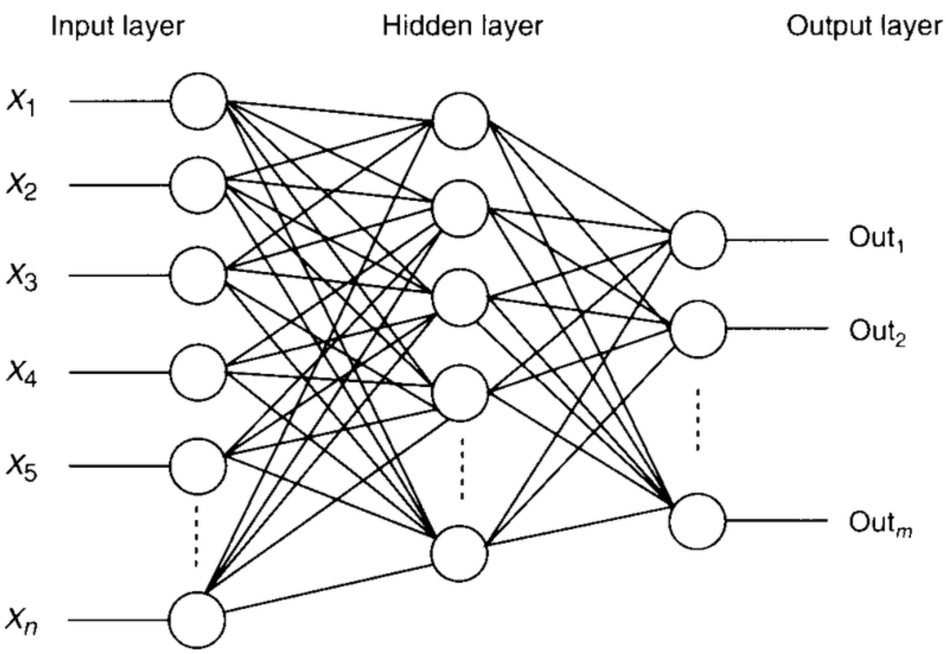

Figure 4: Structure of the Artificial Neural Network (ANN) used in the DSS

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.

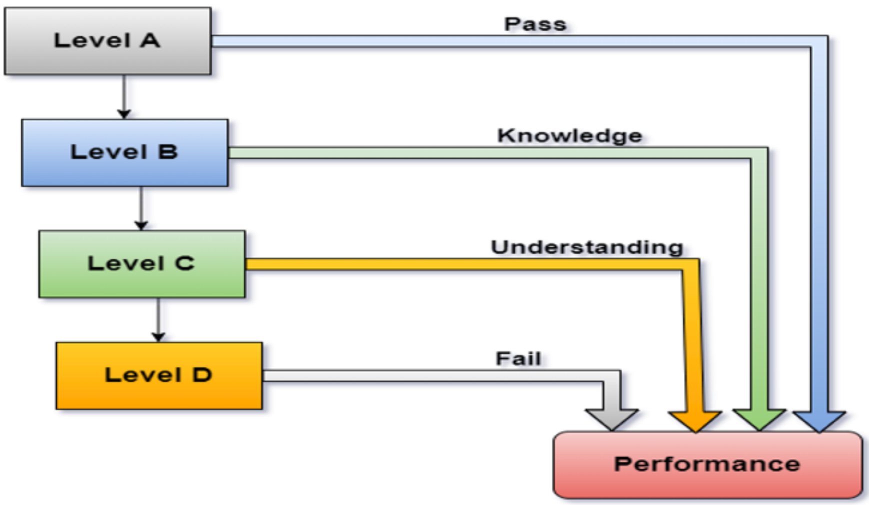

Figure 5: 4-level classification architecture for academic performance evaluation

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

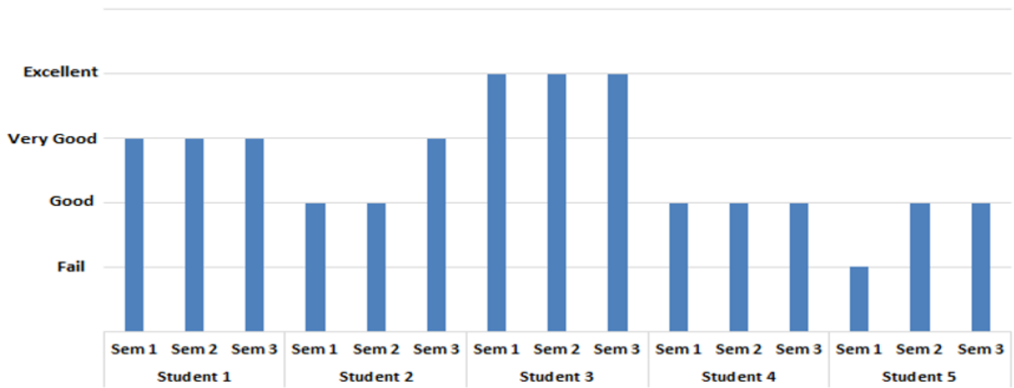

Figure 6: Students' performance across three semesters (exam-wise classification)

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 ±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.

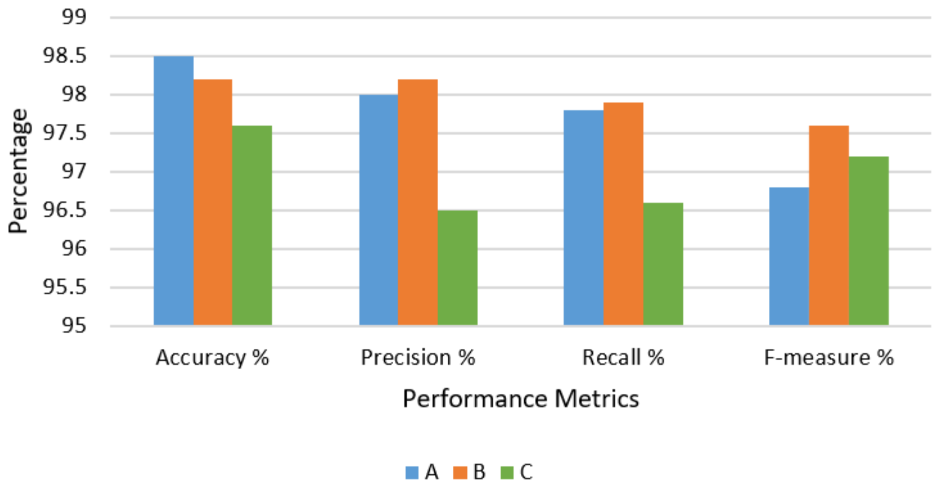

Figure 7: Predicted class distribution based on DSS analysis

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	–	–

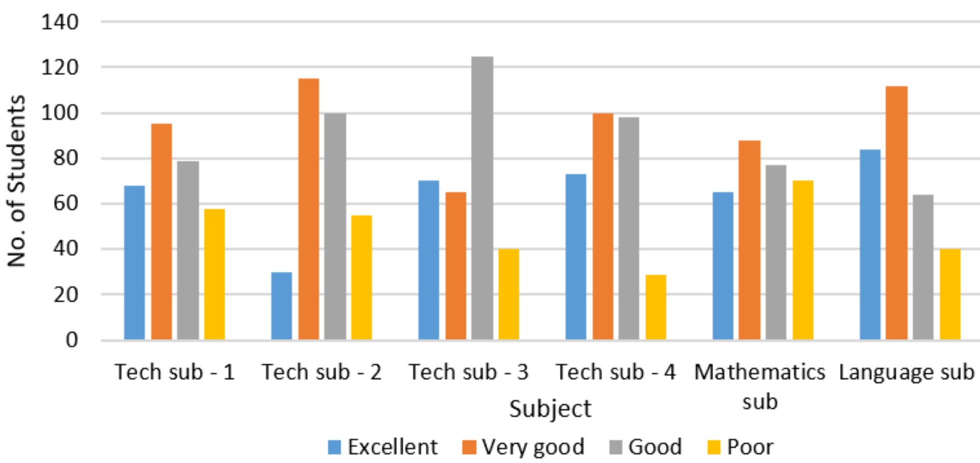

Figure 8: Students' performance in academic subjects

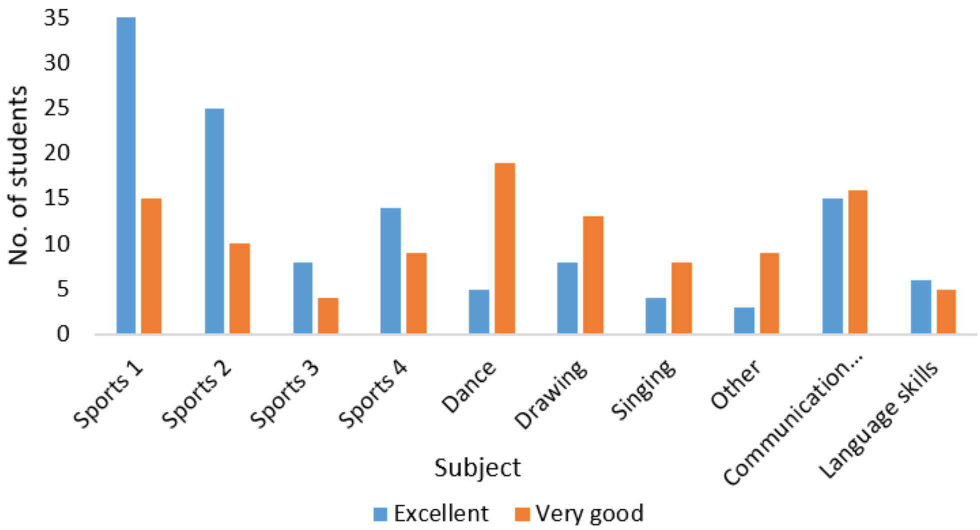

Figure 9: Students' performance in extracurricular activities

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

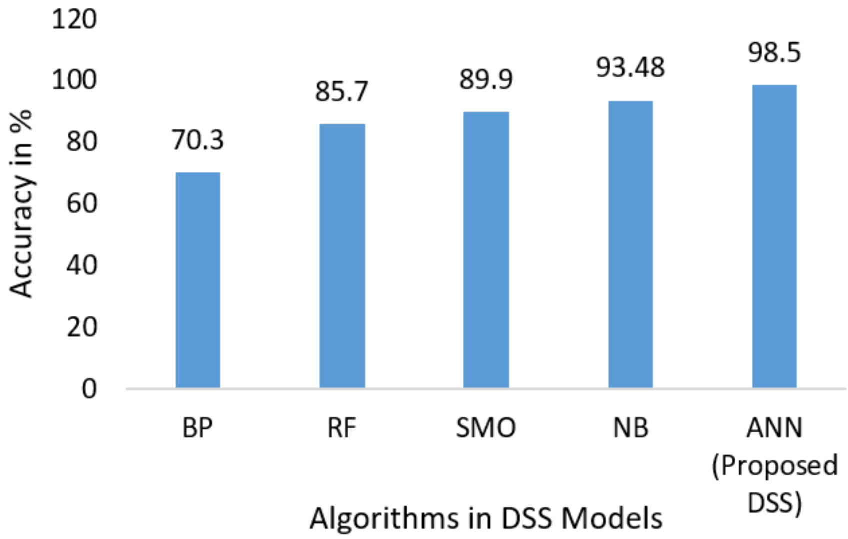

Figure 10: Performance of the proposed DSS model compared to other algorithms

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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