Classification of Student Performance Based on Ensemble Optimized Using Dipper Throated Optimization

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Abstract

Forecasting student performance, sorting students into groups according to their strengths, and working to improve future test scores are all crucial for any institution in today's competitive world. It is important to give students ample notice before a school year begins if they are to be coached to improve their grades by focusing on a certain subject area. Examining this can helps a school significantly reduce its dropout rate. This analysis predicts how well students will do in a given course based on how they did in previous, similar courses. Discovering previously unknown relationships among vast stores of data is the goal of data mining. Insights and forecasts might be gained from these recurring structures. The term "education data mining" describes the assortment of data mining programs used in the educational sector. The primary focus of these tools is on analyzing the information gathered from classrooms and educators. Potential applications of this research include classification and forecasting. It looks into several machine learning methods, including Naive Bayes, ID3, C4.5, and SVM. The experimental analysis uses data collection containing UCI machinery students' grades and other outcomes. Accuracy and error rate are two metrics used to evaluate algorithms.

Keywords: Dipper throated optimization; Neural network; Support vector machine; Decision tree; Voting ensemble.

1. Introduction

Schools must store a massive amount of information to maintain tabs on students, teachers, and classes. There is personal and academic information on students and teachers and course materials, including syllabi, tests, and announcements. The term "educational data mining" [1] is the use of data mining methods to study academic records. Educational data mining is being implemented in a growing number of schools and non-profits better to serve the needs of their students and employees. So that their applications would function properly with their data sets, they have incorporated these methods within them. Below are a few examples of how educational data mining has been implemented.

The success of its pupils is crucial for any school. Students' future academic success [2] can be predicted by past academic accomplishments. The results suggest a possible relationship between students' aptitudes and motivations and their academic success. Teachers may use this sort of data analysis to provide further attention to the students who genuinely need it. The results of their students often evaluate a teacher's effectiveness in the classroom. Every school has to take stock of how well its professors are doing. How well and what kinds of remarks pupils have about their teachers may be

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used to evaluate them. Research of this sort can help a school enhance its pedagogical practices. Assessing the difficulty level requires analysing question papers. These details help a school standardize the grades of its pupils throughout several testing periods.

As shown in Fig. 1, machine learning [3] is essential in mining educational databases. In the field of education, this allows for foresight. This method's strength lies in its ability to spot repeated question patterns. We may estimate how much each topic is typically weighted by analysing past competitive test question papers. Subjects covered in each course vary by semester and sometimes by year. Different problems have no obvious relationship to one another. It is common knowledge that a student's performance in higher-level courses suffers if he has not put in the time to master the basics. Using data mining techniques in education [4 5] can help pinpoint such a cluster of related fields. Students can use this data better to understand the significance of various fields of study. The architecture in Figure 2 shows the overview of this research paper.

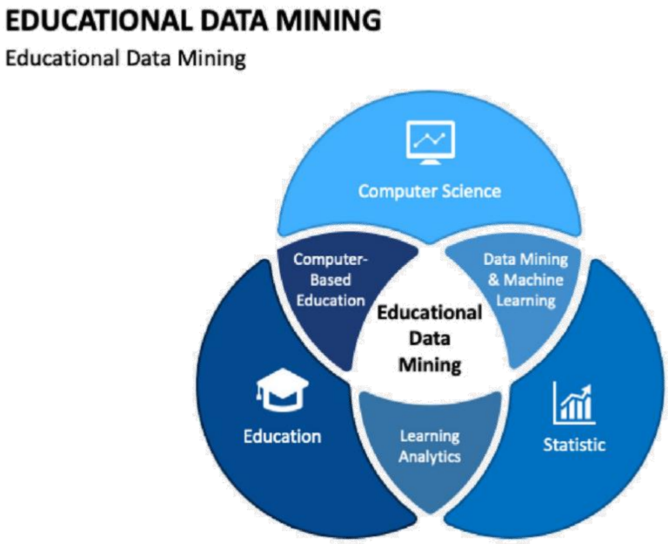

Figure 1: Educational data mining using machine learning.

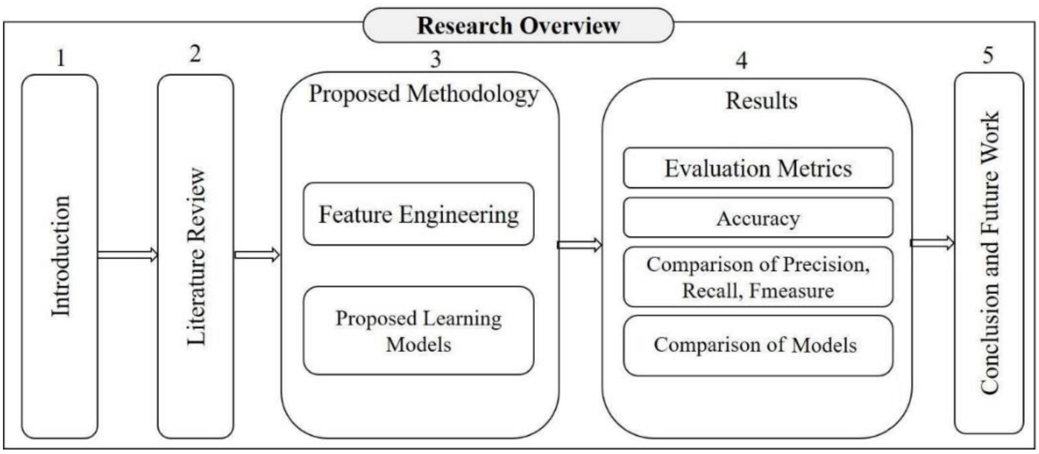

Figure 1: Research Paper Overview.

2. Literature Review

A literature review is a structured strategy for analyzing and assessing existing knowledge in a certain field. Studying existing literature is done to learn how much progress has been made in solving a problem and what options exist for further development. Any issue encountered in the real world is solved little by bit. Using a solution developed by a researcher as a starting point, we may refine it by loosening or doing away with any limiting assumptions. It is important to implement cutting-edge algorithms and data schemes to get similar results in data mining-based research. The limitations of the algorithms we've employed might sometimes be the source of our own limitations. The

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information we've used has certain inherent limits, which impose further restrictions. Before attempting to solve either of these restrictions, it is crucial to conduct a thorough assessment to ascertain whether or not similar enhancements have already been made. There's no use in duplicating research that has already been conducted. All previously proposed ideas must be considered so that their advantages and disadvantages may be weighed. After conducting a literature review, a researcher will have a better idea of where to focus their efforts. The next step is to figure out what needs to be accomplished, after which a method may be proposed. Teachers can benefit from the many types and forms of assessment that have been studied to find the best assessment strategies for their students. It was also decided that technological aid was necessary for evaluating candidates. A rubric has been suggested as the best approach for objectively rating work [6]. Teacher performance evaluation using a recommended method[7] based on a comprehensive analytic hierarchy approach that included both quantitative and qualitative analyses. The degree comparison framework is analyzed to see if it is fair by aiming for a uniform goal and preventing any bias in the subjective evaluation of schools. The missing piece of the puzzle can be found by establishing a link between evaluations and actual results in terms of research. For a more complete picture of the benefits of collaboration between universities and businesses, we conduct a mixed-methods qualitative and quantitative study. Several obstacles have been identified to this partnership, including resistance to change, an elderly academic, a cultural divide, an attitude toward innovation, a propensity toward isolation, and a lack of resources. There are a number of advantages, including increased productivity and the increased employability of graduates [8]. Learning mechanisms were the focus of the studies in [9]. Students have been investigated as topics concerning the benefits they bring to the classroom. It was believed that conducting experiments would pique students' interest and get them interested in the material being studied.

Factor analysis is used to evaluate the student satisfaction index [10], and the model is evaluated and modified based on data from actual students. Rather than the academic standards of teachers or the efficacy of their methods, studies have demonstrated that the availability of instructional technology, materials (especially E-learning), network resources, and instructor supervision significantly impact students' satisfaction levels. We develop and deploy a system for managing the whole teaching and learning process, from coordinating the use of instructional materials to monitoring its efficiency. There are other modules for workflow, a rule engine, and automatic resource allocation in the system [11]. In this study [12], we review data mining methods currently being employed in academic institutions. They found that data mining is an essential resource for those working in the education sector, as it allows for the identification of recurring patterns in information gathered from various sources, including classroom instruction and student performance. The lack of a universal tool that could be used in all school districts is a major hole in the research. Also, teachers can't handle these technologies on their own, thus they need to be included in an online classroom setting. For the purpose of student retention management, research [13] examined the quality of prediction models produced by machine learning algorithms. Decision trees provide more intuitive classification rules than alternative approaches. The results of the experiments showed that the dropout rate may be reduced by using predictive models, which not only identify students who need extra help but also generate an accurate and brief prediction list for their retention. The predicted dropout kids' deficiencies are not obvious enough to facilitate quick remedial actions, which is a gap in the research. Students' academic performance was expected using a number of different factors, and this was explored and analyzed in the method [14]. Comparing several machine learning methods, including Reptree, SimpleCart, Decision table, and J48, it was found that neural network-based classification was the most accurate, followed by Naive Bayes and ID3. On the other hand, multi-strategy machine learning can compensate for many models' weaknesses. The academic performance of students pursuing bachelor's and master's degrees was predicted using two classification methods [15]: a decision tree and a fuzzy genetic algorithm. This served as a feed-forward mechanism for instructors to pay closer attention to at-risk students before it was too late. In addition, it helped find good homes for bright students. The decision tree placed more students in the danger class, but the genetic algorithm found more students who passed because it rated them as safe in the transitional condition between the two extremes.

There is a knowledge gap between the decision tree and the genetic algorithm since the former adopts a pessimistic stance while the latter is wholly positive; this might introduce uncertainty into the results. Every student's low performance has a common lack of individualized attention from the faculty. The course evaluation questionnaires in Framework [16] were scored using ID3 and C4.5 separately to categorize students' strengths and weaknesses across course content and grading scale

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performance. Educators have an advantage in seeing pupils at risk of underachieving and adopting corrective measures before it's too late. Further research revealed that the two approaches produced similar results when working with small data sets, but C4.5 was somewhat more precise than ID3 when dealing large data sets. The experiment can predict future performance problems but can't pinpoint the reasons for them. Analysing and contrasting the best outcomes from numerous prediction algorithms, including the decision tree, C4.5, Naive Bayesian, RIPPER, and SVM. The Naive Bayes approach excels in all of these metrics: FP rate, Precision, F-M, Recall, and MCC. It is yet to be determined whether or not these algorithms are beneficial in improving the quality of education provided in higher learning institutions [17]. To improve the quality management of the teaching and learning process, researchers [18] used a decision tree classification approach on students' assessment data to pinpoint those at risk of low performance. This strategy does not identify students' unique weaknesses, which is a gap in the research. A model [19] was created to classify students into one of two categories based on their performance at the end of their first academic year and to identify important factors that contributed to their success. The model aims to classify students into one of two categories based on academic achievement. It uses data from students' high school performance and their courses taken after completing the first year of study, as well as their rank of preferences submitted to the observed faculty.

3. Proposed Methodology

The proposed methodology is shown in Figure 3. In this figure, three base classifiers were employed. These classifiers are decision trees (DT), multilayer perceptron (MLP), and support vector machines (SVM). These classifiers are used in a voting ensemble model, where the votes are optimized in a hybrid metaheuristic optimization algorithm composed of the dipper throated optimization (DTO) algorithm.

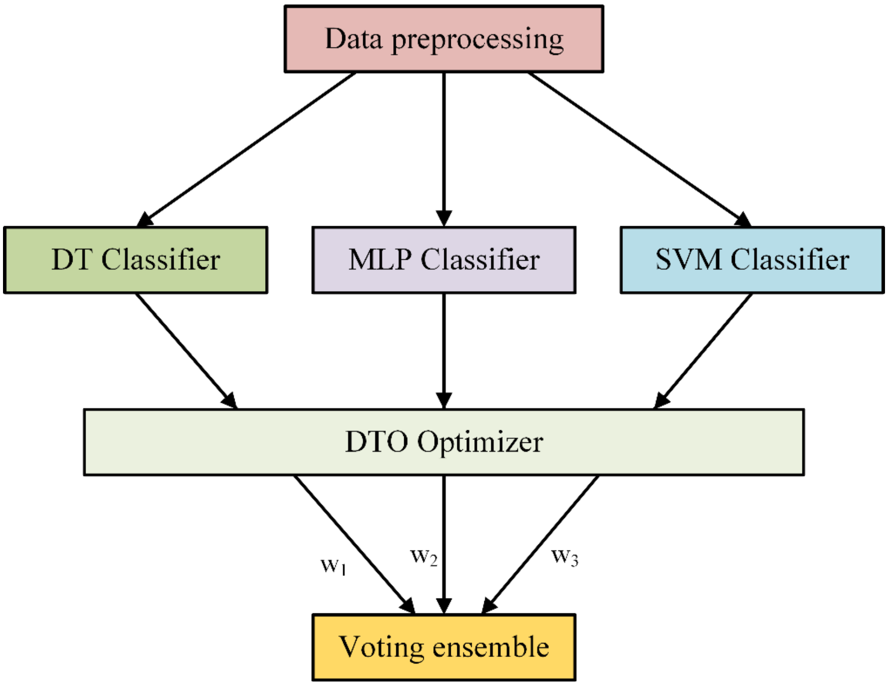

Figure 3: Overview of research methodology.

A. Support Vector Machines (SVM)

Support vector machines (SVMs) are a family of related supervised learning algorithms used for categorization. To rephrase, if it is provided with a set of training samples that have already been classified into one of two groups, it will be able to make predictions about new samples. The SVM training method develops a model for making predictions based on a set of samples classified in a variety of ways. Support vector machines (SVMs) generate a hyperplane or a set of hyperplanes in a high-dimensional space to aid in the categorization process. Figure 4 shows the overall framework of the SVM procedure.

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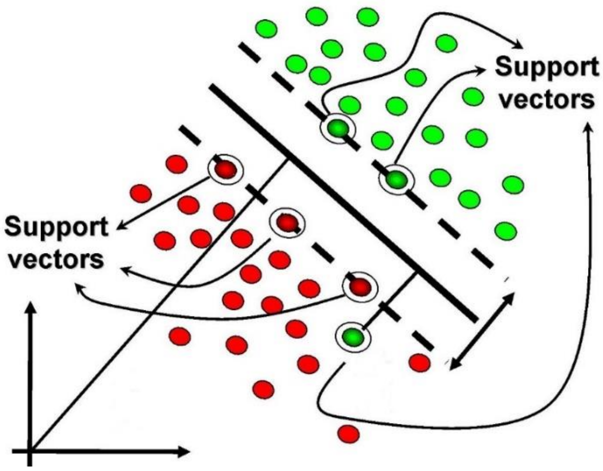

Figure 4: Structure of support vector machines.

B. Multilayer Perceptron (MLP)

When a collection of nodes, or neurons, are linked together via synapses, we have a neural network. Artificial neural networks, which are modeled after the human nervous system, are often employed as estimate models due to their convincing resemblance to the real thing. An input layer, a hidden layer, and an output layer make up the three main components of any artificial neural network. With this method, data is fed into a collection of nodes in the input layer, and an activation function is generated as a result. The hidden layer that gives the inputs their weights sits between the input and output layers. The ultimate output is given by the output layer. Figure 5 depicts the structure of a multilayer neural network.

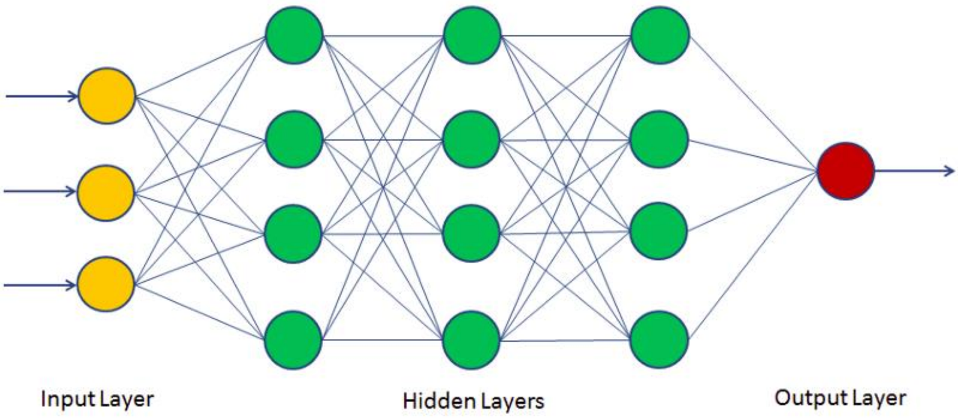

Figure 5: Structure of a multilayer neural network.

C. Decision Trees (DT)

Decision tree learning uses a greedy search to locate optimal nodes within a tree at which to divide and conquer a problem. After the first partitioning, the process is repeated from the top down until all or almost all entries can be placed into the specified buckets. The complexity of the decision tree has a major impact on the possibility that all data points will be clustered together. If you have a short tree, it's easier to extract pure leaf nodes, or data points that belong to a specific class. However, as a tree grows larger, it becomes more challenging to maintain this purity, and as a result, there is often insufficient data contained inside a given subtree. Overfitting is a common consequence of data fragmentation. Since Occam's Razor advocates against "entities being multiplied beyond necessity," the preference for small trees in decision trees is consistent with this principle of parsimony. In other words, decision trees shouldn't grow more complicated than they need to be, because the simplest explanation isn't always the most compelling. Pruning is utilized to achieve both of these aims since it eliminates branches that divide on low-value traits (reducing complexity and preventing overfitting). The accuracy of the model may then be evaluated with the use of cross-validation. When the trees in the ensemble are uncorrelated, the classifier makes more precise predictions, and the random forest methodology is one way to keep the accuracy of decision trees high. Figure 6 shows a diagram of a decision tree's basic structure.

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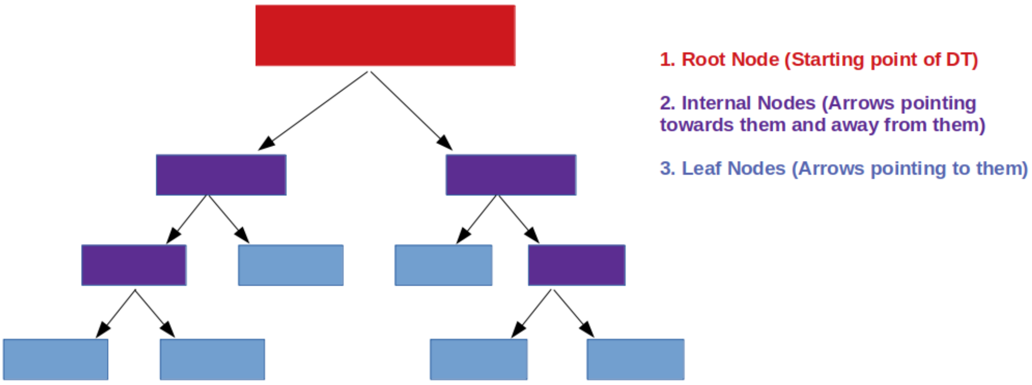

Figure 6: Structure of a decision tree.

D. Dipper Throated Optimization (DTO)

Metaheuristics are used in computer science and mathematical optimization to locate, develop, or choose a heuristic (partial search algorithm) that may offer a good enough solution to an optimization problem, even in the face of faulty knowledge or limited computational resources. A thorough enumeration or exhaustive exploration of all possible answers is impractical, but metaheuristics allow us to sample from this vast pool. Since some metaheuristics may be applicable to a wide range of situations without requiring much pre-planning or specifying too much about the optimization issue at hand, they are often more easily adaptable. The use of metaheuristics, in contrast to optimization algorithms and iterative approaches, does not ensure the discovery of a globally optimum solution for a specific class of problems. Since the solution discovered by many metaheuristics is stochastically optimized, it varies with the produced random variables. Metaheuristics may frequently identify good answers with less computing work than optimization algorithms, iterative approaches, or basic heuristics in combinatorial optimization by searching through a broad range of plausible alternatives. This makes them viable options for resolving optimization issues. Many articles and books have been written about this topic. The vast majority of published works on metaheuristics use an experimental approach, reporting on the author's own implementation and testing of these algorithms in software. Although mostly on convergence and the potential of achieving the global optimum, there are also some formal theoretical conclusions accessible. Recently, a plethora of papers presenting various metaheuristic approaches have been published, each promising to be innovative and useful in practice. Many of the papers in this topic have been of low quality, with problems including ambiguity, inadequate concept development, shoddy research methods, and a failure to acknowledge the work of others.

4. Results

Several libraries for Python3 are used to implement ML models for categorization. NumPy, SciPy, scikit-learn, Keras, pandas, and Matplotlib are just few of the many Python packages available. Scikit-learn has been shown to be the most dependable and user-friendly machine learning library [20-25]. The core of this distribution is provided by the Python packages NumPy, SciPy, and Matplotlib. To measure how well a classifier performs, we need a confusion matrix that shows how often the training data was used to produce inaccurate predictions. Both the observed value and the model's prediction are accurate in the event of a true positive (TP). Both the observed and predicted values are false in a true negative (TN). In Table 1 we can see how the suggested method stacks up against different machine learning models. Using the suggested optimized voting ensemble classifier, the table below displays improved accuracy, sensitivity, specificity, p-value, n-value, and F-score.

Table 1: Classification results using the proposed method compared to other methods

	Accuracy	Sensitivity	Specificity	Pvalue	Nvalue	F-score
NN	0.7407	0.8889	0.6667	0.5714	0.9231	0.6957
SVM	0.7692	0.8889	0.7059	0.6154	0.9231	0.7273
DT	0.8000	0.8889	0.7500	0.6667	0.9231	0.7619
DTO	0.8772	0.8889	0.8696	0.8163	0.9231	0.8511

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The statistical analysis presented in Table 2 shows the superiority of the proposed voting ensemble classifier. These results are better when the proposed optimized voting ensemble is employed.

Table 2: Statistical analysis of the results recorded by the proposed method

	NN	SVM	DT	DTO
Number of values	10	10	10	10
Minimum	0.7307	0.7592	0.8	0.8772
25% Percentile	0.7407	0.7692	0.8	0.8772
Median	0.7407	0.7692	0.8	0.8772
75% Percentile	0.7407	0.7692	0.8025	0.8772
Maximum	0.7507	0.7792	0.82	0.8772
Range	0.02	0.02	0.02	0
10% Percentile	0.7317	0.7602	0.8	0.8772
90% Percentile	0.7497	0.7782	0.819	0.8772
95% CI of median				
Actual confidence level	97.85%	97.85%	97.85%	97.85%
Lower confidence limit	0.7407	0.7692	0.8	0.8772
Upper confidence limit	0.7407	0.7692	0.81	0.8772
Mean	0.7407	0.7692	0.803	0.8772
Std. Deviation	0.004714	0.004714	0.006749	0
Std. Error of Mean	0.001491	0.001491	0.002134	0
Lower 95% CI of mean	0.7374	0.7659	0.7982	0.8772
Upper 95% CI of mean	0.7441	0.7726	0.8078	0.8772
Coefficient of variation	0.6364%	0.6128%	0.8405%	0.000%
Geometric mean	0.7407	0.7692	0.803	0.8772
Geometric SD factor	1.006	1.006	1.008	1
Lower 95% CI of geo. mean	0.7374	0.7659	0.7982	0.8772
Upper 95% CI of geo. mean	0.7441	0.7726	0.8078	0.8772
Harmonic mean	0.7407	0.7692	0.8029	0.8772
Lower 95% CI of harm. mean	0.7374	0.7658	0.7982	0.8772
Upper 95% CI of harm. mean	0.7441	0.7726	0.8077	0.8772
Quadratic mean	0.7408	0.7692	0.803	0.8772
Lower 95% CI of quad. mean	0.7374	0.7659	0.7981	0.8772
Upper 95% CI of quad. mean	0.7441	0.7726	0.8079	0.8772
Skewness	0	0	2.277	
Kurtosis	4.5	4.5	4.765	
Sum	7.407	7.692	8.03	8.772

Comparing the suggested method to the other methods is investigated using the Wilcoxon signed-rank test. Table 3 shows the outcomes of this analysis. It is demonstrated by the p-value in the table.

Table 3: Wilcoxon signed rank test of the recorded results of the proposed method

	NN	SVM	DT	DTO
Theoretical median	0	0	0	0
Actual median	0.7407	0.7692	0.8	0.8772

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Number of values	10	10	10	10
Wilcoxon Signed Rank Test				
Sum of signed ranks (W)	55	55	55	55
Sum of positive ranks	55	55	55	55
Sum of negative ranks	0	0	0	0
P value (two tailed)	0.002	0.002	0.002	0.002
Exact or estimate?	Exact	Exact	Exact	Exact
P value summary	**	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	0.7407	0.7692	0.8	0.8772

Figure 7 is a scatter plot displaying the improvement in classification accuracy over the starting models brought about by the suggested optimal voting ensemble classifier. This diagram illustrates how the improved efficiency of the suggested method.

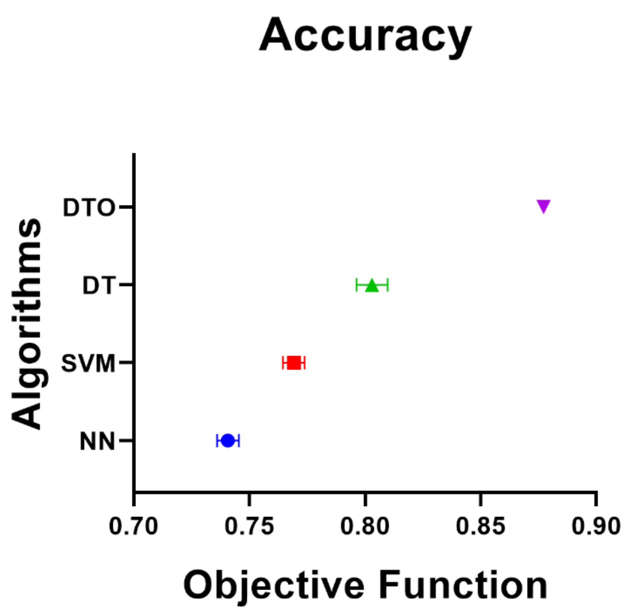

Figure 7: The accuracy of the proposed method compared to other methods

5. Conclusion

Colleges and universities use student achievement as a primary factor for admission. Predicting a student's future success in school is possible by looking at their existing academic record. Findings suggest a possible correlation between students' abilities and motivation. In doing so, educators may better direct their efforts toward helping those students who truly require assistance. Students' achievements are often used as a yardstick to evaluate a teacher's effectiveness. The faculty at every institution has to take a stock. Evaluations of educators can take into account their students' achievements, feedback, and other contributions. Analysis of this sort can help a school enhance its teaching practices. The level of difficulty can be gauged by analyzing past examination papers. The term "education data mining" refers to a suite of programs designed for use in the educational sector. Data analysis from classrooms is the focus of these software packages. The findings of the study might be utilized for labeling or foretelling. Studying the strengths and weaknesses of popular machine learning algorithms including Naive Bayes, ID3, C4.5, and SVM. The experimental study makes use of a data collection containing information about how well UCI students performed on a piece of machinery. Criteria like accuracy and error rate are used to rank algorithms. To correctly categorize a student performance dataset, SVM is the best method.

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References

[1] L. Ji, X. Zhang, L. Zhang, Research on the Algorithm of Education Data Mining Based on Big Data, in: 2020 IEEE 2nd International Conference on Computer Science and Educational Informatization (CSEI), 2020, pp. 344–350.

[2] A. Aleem, M.M. Gore, Educational Data Mining Methods: A Survey, in: 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), 2020, pp. 182–188.

[3] R. Manne, S.C. Kantheti, Application of Artificial Intelligence in Healthcare: Chances and Challenges, Current Journal of Applied Science and Technology 40 (6) (2021) 78–89.

[4] A. Hicham, A. Jeghal, A. Sabri, H. Tairi, A Survey on Educational Data Mining [2014-2019], International Conference on Intelligent Systems and Computer Vision (ISCV) 2020 (2020) 1–6.

[5] S. Kovalev, A. Kolodenkova, E. Muntyan, Educational Data Mining: Current Problems and Solutions, V International Conference on Information Technologies in Engineering Education (Inforino) 2020 (2020) 1–5.

[6] S.R. Hamidi, Z.A. Shaffiei, S.M. Sarif, N. Ashar, Exploratory study of assessment in teaching and learning, International Conference on Research and Innovation in Information Systems (ICRIIS) (2013) 398–403.

[7] J. Li, J. Zhao, G. Xue, Design of the index system of the college teachers’ performance evaluation based on AHP approach, International Conference On Machine Learning And Cybernetics, Guilin: IEEE 2018 (2011) 995–1000.

[8] K. Ramakrishnan, N.M. Yasin, Higher learning institution — Industry collaboration: A necessity to improve teaching and learning process, in: 6th International Conference on Computer Science & Education (ICCSE), 2011, pp. 1445–1449.

[9] Staron, M., (2007), Using Experiments in Software Engineering asan Auxiliary Tool for Teaching – A Qualitative Evaluation from the Perspective of Students’ Learning Process’, 29th International Conference on Software Engineering, ICSE 2007, pp. 673 – 676.

[10] X. Feng, G. Hui, Study on the Evaluation Model of Student Satisfaction Based on Factor Analysis, International Conference on Computational Intelligence and Software Engineering (CiSE) (2010) 1–4.

[11] Abdelhamid, A.A.; El-Kenawy, E.-S.M.; Khodadadi, N.; Mirjalili, S.; Khafaga, D.S.; Alharbi, A.H.; Ibrahim, A.; Eid, M.M.; Saber, M. Classification of Monkeypox Images Based on Transfer Learning and the Al-Biruni Earth Radius Optimization Algorithm. Mathematics 2022, 10, 3614.

[12] Eid, M.M.; El-Kenawy, E.-S.M.; Khodadadi, N.; Mirjalili, S.; Khodadadi, E.; Abotaleb, M.; Alharbi, A.H.; Abdelhamid, A.A.; Ibrahim, A.; Amer, G.M.; Kadi, A.; Khafaga, D.S. Meta-Heuristic Optimization of LSTM-Based Deep Network for Boosting the Prediction of Monkeypox Cases. Mathematics 2022, 10, 3845.

[13] Hua, Z., Xue-qing, L., Jie-cai, Z., & Jiang-man, X. (2009), ‘Research and implementation of Course Teaching learning Process Management System’, IEEE International Symposium on IT in Medicine & Education, ITIME ’09., Vol. 1, pp. 865 – 871.

[14] D.K. Gautam et al., ‘Accreditation of engineers for effective implementation of the Washington accord’, Achieving excellence through Accreditation, First world summit on accreditation WOSA-2012, NBA, New Delhi, 2012, pp. 1–15.

[15] S. Yadav, B. Bharadwaj, S. Pal, Mining Education Data to Predict Student’s Retention: A comparative Study Retrieved from Retrieved from International Journal Of Computer Science And Information Security 10 (2) (2012) 113–117.

[16] K. David Kolo, S. A. Adepoju, J. Kolo Alhassan, A Decision Tree Approach for Predicting Students Academic Performance, International Journal Of Education And Management Engineering 5 (5) (2015) 12–19.

Doi: https://doi.org/10.54216/JAIM.020104
Received: April 20, 2022 Accepted: October 15, 2022

[17] V. Dhanalakshmi, D. Bino, A. Saravanan, Opinion mining from student feedback data using supervised learning algorithms, in: 3rd MEC International Conference on Big Data and Smart City, Piscataway, New Jersey, IEEE, 2016, pp. 1–5.

[18] A.B. Raut, A.A. Nichat, Students Performance Prediction Using Decision Tree Technique, International Journal of Computational Intelligence Research 13 (7) (2017) 1735–1741.

[19] P.V.V.S. Eswara Rao, S.K. Sankar, Survey on Educational Data Mining Techniques, International Journal Of Engineering And Computer Science (2017).

[20] G. Kavitha, L. Raj, Educational Data Mining and Learning Analytics Educational Assistance for Teaching and Learning, International Journal Of Computer & Organization Trends 41 (1) (2017) 21–25.

[21] J. Mesaric´ , D. Šebalj, Decision trees for predicting the academic success of students, Croatian Operational Research Review 7 (2) (2016) 367–388.

[22] https://archive.ics.uci.edu/ml/datasets/Student+Performance.

[23] El-kenawy, El-Sayed M., Hattan F. Abutarboush, Ali Wagdy Mohamed, and Abdelhameed Ibrahim. "Advance artificial intelligence technique for designing double T-shaped monopole antenna." CMC-COMPUTERS MATERIALS & CONTINUA 69, no. 3 (2021): 2983-2995.

[24] A. A. Abdelhamid and S. R. Alotaibi, "Optimized two-level ensemble model for predicting the parameters of metamaterial antenna," Computers, Materials & Continua, vol. 73, no.1, pp. 917–933, 2022.

[25] El-Kenawy, El-Sayed M., Seyedali Mirjalili, Fawaz Alassery, Yu-Dong Zhang, Marwa Metwally Eid, Shady Y. El-Mashad, Bandar Abdullah Aloyaydi, Abdelhameed Ibrahim, and Abdelaziz A. Abdelhamid. "Novel Meta-Heuristic Algorithm for Feature Selection, Unconstrained Functions and Engineering Problems." IEEE Access 10 (2022): 40536-40555.

Doi: https://doi.org/10.54216/JAIM.020104
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