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A Data Mining and Fuzzy Logic Hybrid Model for Enhancing Instructional Quality and Student Success in Higher Education

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***Abstract* – Teaching standards and programs for professional development of teachers are only two of the many innovations that public schools have introduced over the last 20 years to improve educational performance. The most important component impacting student achievement—Instructional Quality—is not fully captured by standardised test scores, which have long been the principal indicator of reform success. Few educational assessments track the quality of instruction, even though it has a significant impact on student success. In order to assess and enhance the quality of instruction through data-driven means, this study suggests a multi-stage methodology. Data cleansing, missing value handling, feature engineering, and EDA are all part of the preprocessing phase. They present Fuzzy HTWSVM, a new classification model that enhances prediction accuracy by integrating fuzzy logic with HTWSVM. A grid search is used to optimise the model by refining parameters and improving performance. The Fuzzy HTWSVM model achieves a high classification accuracy of 96.25%, reduces prediction errors, and provides more trustworthy insights into the effectiveness of training, according to evaluation results, outperforming previous approaches. These results show that the model can be a useful tool for evaluating and improving the quality of education, which can lead to better Student Success.**

Keywords—Exploratory Data Analysis (EDA), Natural Language Processing (NLP), Gated Recurrent Unit (GRU), Decision Tree Classification (DTC).

I. INTRODUCTION

Instructional quality students success like are showing a growing interest in online learning therefore it's crucial that it figure out what factors lead to positive student outcomes like success. The involvement of the educator was uncovered in this investigation as an extra component that has been under- or even ignored in prior research. Based on what it know so far it seems that the instructor's position is an additional variable that can improve the online learning formula but this aspect has only been studied in passing. Furthermore, there is a dearth of literature particularly in the realm of higher education that investigates the relationship between student achievement and instructor and course quality in online settings [1]. Students success online courses need more research on instructor and instructional quality since these factors have been shown to significantly affect student performance in traditional classroom settings in some cases these factors have even outperformed a combination of demographic variables. Focusing on learning in a digital setting most teachers have honed their skills in more conventional classroom settings [2]. This is significant when thinking about student achievement since in most circumstances the instructor has a direct correlation to the knowledge that students learn. When it comes to online instruction in student's success what works in the classroom may not always translate to the virtual classroom. In response to the explosion of online learning options over the last several decades both schools and teachers have worked to establish criteria for evaluating the quality of these programs [3]. Online courses are courses that allow students to learn at a distance and potentially at any time through the use of various technologies. They are just as effective as in-person courses and are experiencing a continuous increase in demand. There is a growing need for proven methods to guarantee high-quality online courses and programs and to guide practice as the use of online learning becomes more commonplace in higher education.

Although many practitioners find practices by collecting tales and experiences from instructors researchers perform studies to find practices that are supported by evidence and can be used by instructors. It is important to find out what makes a good class and then show how those things affect the results student success. Thus it is necessary to gain a deeper understanding of the connection between various pedagogical approaches and outcomes achieved by students [4]. Improving our knowledge of the strategies that benefit both traditionally underserved and majority student populations is essential. Research on student demographics and how such demographics impact course perceptions linkages to student outcomes is currently lacking. While acknowledging the substantial challenges that under-represented students may have while trying to engage in and finish online courses assert that they are not aware of any research that investigates the rise in enrolment of such students. Important motivating traits that are believed to influence both the quality of instruction and students' ideas about what motivates them to learn. Teachers' levels of instructional quality have also been linked to student motivation learning and achievement [5].

The remainder of this work is structured as follows. The literature review is presented in Section II. Section III provides a comprehensive description of the gene expression datasets. A Fuzzy HTWSVM method is employed to identify a reduced set of variables that substitute the original high-dimensional variables for training purposes. Section IV details the numerical experiment conducted to assess the predictive performance of our technique. Ultimately, the results and discussions of the work are presented in Section V.

II. Literature Survey

Analyzing data and seeing patterns has shown revolutionary promise in multiple fields The purpose of this research is to improve student success teaching quality assessment and address these CNN. The DL models have made great strides in many fields, including computer vision and NLP. It aims to provide strong data-driven insights to help institutions improve pedagogical approaches and course design by utilizing DL technologies. The goal of using the model's automated analysis is to find hidden problems and ways to improve the quality of education [6]. In order to make teaching quality assessments more accurate and reliable, this study presents a DL method that uses CNN. The proposed approach provides strong backing for assessing and bettering the quality of teaching at universities by combining various data sources and making use of sophisticated ML techniques. This study seeks to provide a more accurate evaluation framework by incorporating DL technologies. The goal is to improve the impartiality and precision of assessments make personalized feedback simpler and encourage creativity in instructional methods. The goal of AI is to give computers the ability to think and reason like humans [7]. Applications of AI are expanding across all sectors including agriculture, industry, medicine and education due to AI systems' ability to learn from previous experiences or outcomes and make decisions based on these. A subsystem of AI is ML computer programs that learn from data allow teachers to keep tabs on their pupils' progress in class and intervene before they fall behind. The use of AI in higher education institutions has the potential to raise the bar for educational achievement, according to research [8].

A state-of-the-art DL model designed to detect pupils who are falling short of educational goals was the focus of this research. The goal was to help schools identify children who needed extra help in the classroom by using a complex GRU with characteristics including thick layers, max-pooling layers and the ADAM optimization algorithm [9].It constructs and evaluates the following prediction models using a large dataset that includes demographic, socioeconomic, academic and financial variables: LR, RF, DTC, SVM and Gradient Boosting. In order to help educational institutions intervene more effectively our prediction algorithm seeks to identify students who are very likely to drop out. Enhancing the possibility for student success these interventions can be tailored to meet the unique requirements and obstacles encountered by at-risk pupils. However by utilizing ML techniques like ANN the shortcomings of traditional methodological approaches have been effectively addressed in the categorization of diverse educational outcome this study built MLP and ANN models using a BP algorithm [10]. They employed a structured ANN based method to deduce the patterns of variables that predict educational achievements in higher education [11]. As part of this strategy strong theoretical models are taken into account while designing the NN structure that directs the predictor selection. The use of AI in universities has enormous promise for bettering the educational experience of students from other countries. Implementing AI systems to maximize their benefits while addressing the unique requirements and problems of international students requires careful analysis of the risks and benefits [12].

Fuzzy HTWSVM, a unique SVM model that combines fuzzy HTWSVM with hypersphere SVM, is introduced in this research. Three important points are made in this article. To begin, in order to minimise the impact of outliers on the ideal classification surface, they utilise the hypersphere SVM with the smallest radius to incorporate as many data as possible into the high-dimensional space. Second, to lessen the effect of outliers, they compute the membership degree for various samples using the distance-based factor function. In the third phase to enhance classification accuracy, grid search is employed to optimise the model's parameters inside the parameter space. The use of several performance metrics, including accuracy and ROC, demonstrates that Fuzzy HTWSVM markedly enhances classification performance across eight cancer datasets, exhibiting reduced prediction error relative to other classifiers.

III. Proposed System

Some in the academic community wonder if and how it is possible to disentangle the evaluation of class performance from students' happiness and achievement. As they delve into these concerns, higher education professionals should think about what was important for a good education in the days before computers and how those factors might or might not play a role in today's classrooms.

The 2019 dataset is based on responses from 145 college students in Cyprus. The following structure is used to express the obtained data by way of 31 variables:

Individual enquiries comprise variables 1 through 10.

The student's family is the subject of variables 11–16.

The last set of variables concerns academic routines [13].

Data collection and preprocessing, feature correlation analysis and selection, modelling, and the study diagram are all depicted in Figure 1 [14].

A. Data Preprocessing:

Consistency and cleanliness are prerequisites for guaranteeing the dependability of raw data, which is critical to its utility. Problems including inconsistency, incompleteness, and errors are common in real-world data. Data pre-processing makes use of a variety of approaches to address these concerns, improving the predictive power of models. The data was pre-processed in a number of ways to guarantee it was of high quality and applicable for analysis [15].

1) Cleaning the Data:

Keeping data accurate and avoiding skewed analytical results by checking for duplicates in the dataset. No duplicate values were found in the Kaggle dataset or the survey data set.

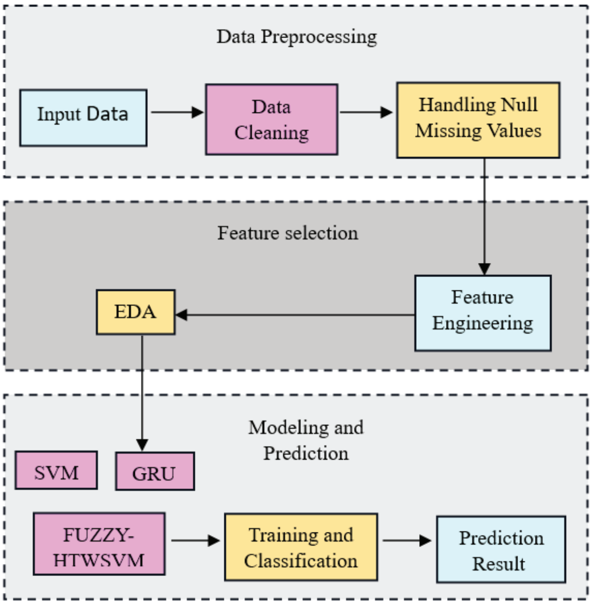

Fig. 1. The Proposed Framework

1) Missing and Null Values Handling:

Utilising Python to ascertain the presence of any null or missing values within the collection. The Kaggle dataset and the survey dataset contained no missing values.

2) Feature Engineering:

Features were assessed according to their pertinence to the target variable. Only pertinent elements from both the Kaggle dataset and survey data were included, with certain aspects amalgamated for enhanced analysis. The survey data is formatted for modelling and various variable combinations by transforming categorical variables into a numerical format through methods such as one-hot encoding.

B. EDA and Feature Engineering:

Fields of floral engineering were used to evaluate feature importance for predictive modelling. A significance value (JN_j) was allocated to each feature W_j utilising a Fuzzy HTWSVM model. Equation *(1)* also makes use of ElasticNet, an LR model that combines $K2$ and $K2$ regularisation, for feature extraction [16].

$$\hat{\theta} = Arg \min_{\theta} \left(\frac{1}{2n} \|y - X\theta\|_2^2 + \tau\alpha\|\theta\|_1 + \frac{\tau(1-\alpha)}{2} \|\theta\|_2^2 \right) \quad (1)$$

The α regularisation strength is determined by τ, the $\frac{1}{2}K1/K2$ ratio is regulated by θ, and Y_j is the response variable.

In EDA, statistical and visualisations analysis are used to uncover the underlying patterns in a dataset. This helps to spot outliers and provides a comprehensive understanding of the dataset's structure. The data was meticulously compiled to create a stable and refined dataset, laying the framework for future examinations.

C. Model Training:

1) Fuzzy HTWSVM:

With the goal of improving classification accuracy while simultaneously decreasing training dataset noise, it present a new model called the Fuzzy HTWSVM, which combines the fuzzy technique with the hyper sphere SVM.To begin, they use the hypersphere SVM method to find the sphere's centre and radius. Subsequently, the samples located outside the sphere are eliminated, and a new set is produced within the sphere. The subsequent step involves calculating the fuzzy factor for each sample, indicating the extent of its membership in the respective class, utilising a distance-based fuzzy function. Ultimately, Fuzzy HTWSVM is employed to address the optimisation challenge of the hyperplane classification.

Formula (2) lays down the parameters for the hypersphere SVM method, which aims to find a hypersphere with the minimum radius that covers the most samples in three-dimensional space [17].

$$\min_{\gamma} Q^2 + D \sum_{j=1}^{k} \omega_j \; s.t. \left\|\varphi(w_j) - b\right\|^2 \leq Q^2 + \omega_j, \omega_j > 0 \quad (2)$$

Let b be the number of training samples, Qrepresent the radius of the sphere, k signify the centre of the sphere, and D be the regularisation parameter that governs the penalty for misclassified samples.

As a result of all training samples having the same effect on the ideal classification surface, noise cannot be reduced. On the other hand, in reality, various training sample locations have varied impacts on the ideal classification surface. To enhance the accuracy of categorisation, they introduce a fuzzy factor that is based on distance and represents the degree of membership. The significance of the sample inside the sample set is indicated by the Euclidean distance between the sample and the class centre.

Consider two classes: one with w as its centre and the other with w as its centre. Then $q_1 = max\left\|w_j - w\right\|, j = 1,2,..,k_1; q_2 = max\left\|z_j - z\right\|, j = 1,2,..,k_2$. The formula $r(w_j) = 1 - \frac{\|w_j - w\|}{q_1} + \tau; r(z_j) = 1 - \frac{\|z_j - w\|}{q_1} + \tau$ can be used to find the membership degree of each sample. τ The following distance-based fuzzy factor is obtained when is a given tiny positive in Equation (3).

$$r(w_j) = \begin{cases} 1 - \dfrac{1}{1 + (Q_1^2 - c_{jB}^2) + \tau}, & w_j \in B \\ 1 - \dfrac{1}{1 + (Q_2^2 - c_{jA}^2) + \tau}, & w_j \in A \end{cases} \quad (3)$$

The fuzzy sample set $\{(w_j', z_j', r_i)\}$ $(0 \leq r_j \leq 1, j = 1,2,,.o)$is obtained using the factor.

Hence, equation (4) contains the solution to the hyperplane's optimisation issue using Fuzzy HTWSVM:

$$\begin{cases} \min\limits_{x_1 a_1 \varphi_1} \dfrac{1}{2}\|Bx_1 + f_1 + a_1\|_2^2 + d_1 r_2^S \varphi_1 \\ s.t - (Ax_1 f_1 + a_1) + \varphi_1 \geq f_2\varphi_1 \geq 0 \\ \min\limits_{x_2 a_2 \varphi_2} \dfrac{1}{2}\|Bx_2 + f_2 + a_2\|_2^2 + d_2 r_2^S \varphi_2 \\ s.t - (Ax_2 f_2 + a_2) + \varphi_2 \geq f_2\varphi_2 \geq 0 \end{cases} \quad (4)$$

$r1$ *and* $r2$ represents the fuzzy vector of samples in sets B and A of categorisation. The membership degree of each sample is multiplied by its inaccuracy. The Lagrangian function is employed to derive the dual problem of Equation (5).

$$\begin{cases} \min\limits_{\gamma} \gamma^S H(G^S G)^{-1} H^S \gamma + f_2^S \gamma s.t. 0 \le \gamma \le d_1 r_2 \\ \min\limits_{\gamma} \alpha^S H(H^S H)^{-1} G^S \alpha + f_2^S \alpha s.t. 0 \le \alpha \le d_2 r_1 \end{cases} \quad (5)$$

A comprehensive description of Fuzzy HTWSVM is provided in Algorithm 1.

Algorithm1: The Algorithm for Fuzzy HTWSVM Model	
Input:	Sample set of Training $\{(w_j . z_j), j = 1,2,..k\ w_j \in Q^m\}, k = k_1 + k_2, w_i = (i = 1,2,..k_1)$ includes both positive and negative samples.The matrices of the positive and negative samples of the training set are represented by B and A, respectively.
Output:	The hyperplanes for classification.
1.	With the help of Equation (2), everyone can determine the centres of the two types of training sample points on the sphere, b_1 and b_2 .The hyperspheres radii, Q_1 and Q_2 are computed.
2.	By deleting the data points that are located outside of the hyperspheres, a fresh training set of samples is created. $B' = k_1' \times m, k_1' < k_1, A' = k_2' \times m, k_2' < k_2$
3.	With the help of the distance $c_{jB}^2 = \lVert \delta(w_j) - b_1 \rVert^2, c_{jA}^2 = \lVert \delta(w_j) - b_2 \rVert^2$ in relation to the two types of sample sets and the points on a sphere. $r(w_j) = \begin{cases} 1 - \dfrac{1}{1 + (Q_1^2 - c_{jB}^2) + \tau}, & w_j \in B \\ 1 - \dfrac{1}{1 + (Q_2^2 - c_{jA}^2) + \tau}, & w_j \in A \end{cases}$ does not change. Setting up the procedure to obtain the component. $r_j(0 \le r_j \le 1, j = 1,2,,.k)$
4.	The Sample set of Fuzzy $\{(w_j', z_j', r_i), j = 1,2,..q, w_j \in Q^m, z_j = \pm 1\}$ is obtained.
5.	Equation (5) is used to train the fuzzy sample sets B' and A', and then the best classification hyperplanes are obtained.

IV. Result and Discussion

Important aspects of the educational process and their effect on students' cognitive results are discussed in this chapter. The underlying hypothesis was that the quality of the teacher has a direct correlation with the quality of the education and, by extension, the achievement of the students. It is hard to make generalisations because the strength of these links may differ among nations. Nonetheless, patterns of relationships that are comparable may be visible in different parts of the globe. Using multi-level structural equation modelling on data collected from fourth grade teachers and students, these hypotheses were tested.

Figure 2 illustrates the proposed Fuzzy HTWSVM technology in relation to data amount and execution time, alongside other established methodologies. The correlation between execution durations in seconds and data sizes can be illustrated by plotting the x-axis against a range of 2000 to 200,000 on the y-axis.

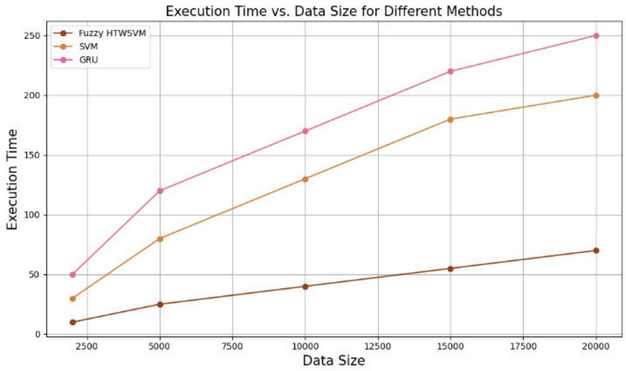

Fig. 2. The Different Model Execution Time

TABLE I. Evaluation Metrics

Model	MAE	MSE	R^2
SVM	5.268	10.112	0.521
Fuzzy HTWSVM	**2.143**	**8.127**	**0.643**
GRU	8.368	`0.343	0.578

Table 1 represents the evaluation metrics for the GRU Model, the Fuzzy HTWSVM, and the SVM, respectively. According to Table 1, the Fuzzy HTWSVM Model outperforms the other two models.

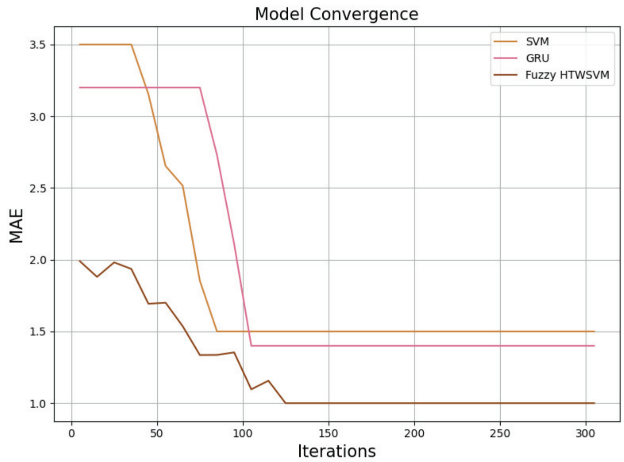

Fig. 3. MAE Error Situation

The application of Fuzzy HTWSVM for evaluating instructional levels eliminates the necessity for a sophisticated mathematical model, addressing the nonlinear assessment challenges and effectively mitigating the shortcomings of conventional evaluation approaches. Figure 3 illustrates the faults of various algorithms.

TABLE II. Performance Metrics (%)

Models	Accuracy	Precision	Recall	F1-Score
SVM	91.34	89.76	88.68	91.51
Fuzzy HTWSVM	**96.25**	**94.28**	**93.57**	**96.43**
GRU	93.87	91.38	90.34	93.92

Student performance evaluations show that the suggested model works better, and the model also has excellent assessment accuracy levels. Table 2 displays the levels of accuracy, precision, and recall.

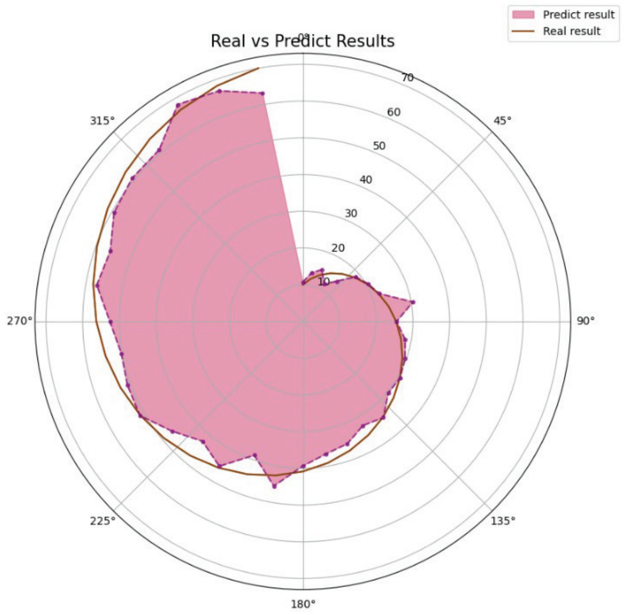

Fig. 4. Comparsion of Fuzzy HTWSVM Prediction

The tie prediction error was computed, resulting in the prediction curve depicted in Figure 4.

TABLE III. COMPREHENSIVE PERFORMANCE (%)

Metrics	SVM	Fuzzy HTWSVM	GRU
MCC	0.9126	0.963	0.9364
G-means	0.9272	0.9728	0.9453
Specificity	0.9120	0.9621	0.9352
Log Loss	0.2214	0.0281	0.2648
Kappa	0.9118	0.9615	0.9341

Table 3 shows the results of a thorough study of our suggested method's performance compared to other methods found in the literature. The outcomes are widely.

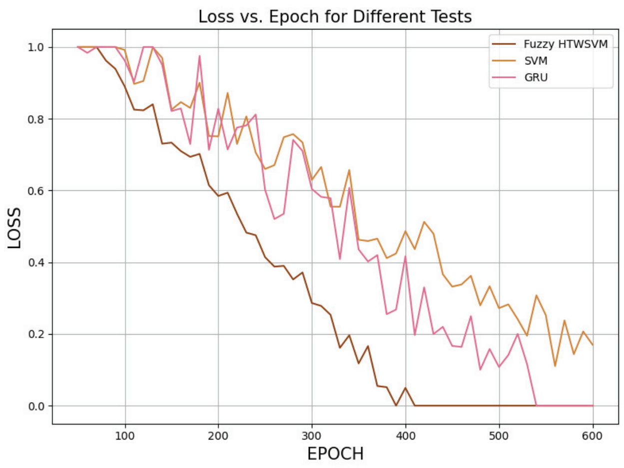

Fig. 5. Model Convergence

The learning iterations amount to 600, with an error margin of 0.001. Subsequent to the construction of the Fuzzy HTWSVM, the network undergoes training. The acquired model is evaluated, and the model's convergence is illustrated in Figure5.

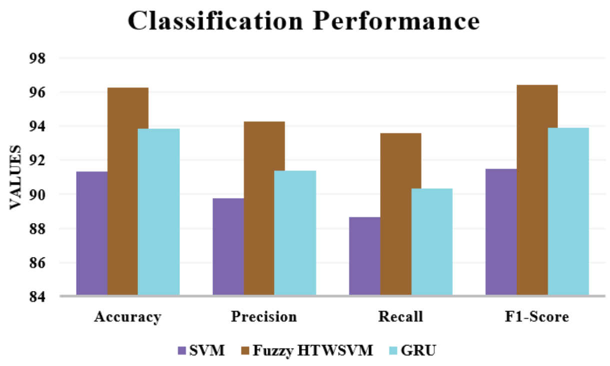

Fig. 6. Classification Performance

Visualizing the classification performance of three classifiers is shown in Figure 6, which allows one to observe the impact of different models on performance. In four performance indicators, the superiority of the Fuzzy HTWSVM methodology over other methods is more readily apparent.

V. CONCLUSION

Every year, students in secondary school have a wide variety of instructors from whom they study and engage. Nevertheless, due to the challenges in collecting data on students as they move between classes, education research mostly concentrates on the relationship between instruction and student learning in a single classroom. So, most of what it know about the connections between teaching, student motivation, and learning comes from comparing students within the same class or across classes. While useful, a more robust strategy would involve comparing students' education in two separate classrooms and then looking for correlations with outcomes in both of those groups. Data quality is achieved by preprocessing activities such as data cleansing, handling of missing and null values, and feature engineering. Feature engineering and EDA were used to extract the features. The Fuzzy HTWSVM is an innovative classification model that combines the Fuzzy HTWS VM with the hypersphere SVM. Lastly, all samples are trained using Fuzzy HTWSVM with parameters optimised by grid search. In comparison to other models, the suggested one has an accuracy of 96.25%. The assessment findings demonstrate that the suggested method can enhance classification performance and decrease dataset prediction errors.

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