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VITAL SIGNS-BASED ENGINEERING STUDENTS' STRESS LEVEL PREDICTION AND IMPACT ANALYSIS ON ACADEMIC PERFORMANCE USING A2RQNFIS

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Abstract: For improving the engineering students' academic performance, their stress level is predicted. But, the prevailing works didn't focus on calculating engineering students' stress index based on important vital signs. Thus, vital signs-based engineering students' stress level prediction and impact analysis on academic performance using Adaptive Arctangent Rational Quadratic Neuro-Fuzzy Inference System (A2RQNFIS) are presented in this paper. Firstly, students' stress level data are taken; then, they are cleaned. Afterward, by using Density-Based Bray-Curtis Matusita Spatial Dunn Hubert Clustering of Applications with Noise (DB2MSDHCAN), pattern analysis is performed. Thereafter, by employing the Erlang Gompertz Kalman Filter (EGKF), temporal dynamic analysis is done. Similarly, from cleaned data, a spider plot is constructed. Next, from the plot and temporal dynamic analysis outcomes, features are extracted. Likewise, based on the vital signs, the stress index is calculated. Similarly, from Students' Academic Stress Questionnaires (SASQ), the stress score is estimated. Then, the stress level of engineering students is predicted based on the extracted features, stress index, and stress score by using A^{2}RQNFIS. Next, by using coping strategies, stress management suggestions are provided. Similarly, by using A^{2}RQNFIS, the academic performance of engineering students is predicted. Afterward, by using the Pearson Correlation Coefficient (PCC), correlation analysis is done. Students are highly impacted if the correlation is high. Students are less impacted if the correlation is low. As per the results, the proposed model achieves a high accuracy of 98.68%, which is superior to the prevailing techniques. **Keywords:** Vital signs, Adaptive Arctangent Rational Quadratic Neuro-Fuzzy Inference System (A^{2}RQNFIS), Density-Based Bray-Curtis Matusita Spatial Dunn Hubert Clustering of Applications with Noise (DB^{2}MSDHCAN), Erlang Gompertz Kalman Filter (EGKF), Pearson Correlation Coefficient (PCC), Coping strategies, and Students' Academic Stress Questionnaires (SASQ).

1. INTRODUCTION

Usually, stress is the psychological and emotional pressure experienced by students during their academic period (Liu et al., 2024). Lack of sleep, fear of low grades, and high levels of competition may be experienced by students, which causes stress to the students (Bork & Mondisa, 2022). Similarly, stress can exacerbate other mental health issues in students (Parthiban et al., 2021). Also, engineering students experience anxiety disorders as twice much as other college students (Sergio et al., 2024). But, high stress affects the academic performance of students (Jensen & Cross, 2021). Thus, to predict the stress level of students, many Artificial Intelligence (AI) techniques are established (Morales-Rodríguez et al., 2021).
To predict the stress level of students, Machine Learning (ML) techniques like KNN, RF, decision tree, and SVM were employed in existing studies (Siddique S et al., 2021) (Geronimo et al., 2023). Similarly, for correlation analysis, some researchers employed Structural Equation Modeling (SEM) (Deng et al., 2022). Moreover, for students' academic performance prediction, ensemble-based classifiers were utilized (Siddique A et al., 2021).But, the existing studies didn't concentrate on calculating the stress index based on important vital signs. Thus, this paper proposes vital signs-based engineering students' stress level prediction and impact analysis on academic performance using A^{2}RQNFIS.

1.1 Problem Statement

❑ None of the prevailing works concentrated on calculating engineering students' stress index based on four important vital signs, namely temperature, SpO2, heartbeat, and respiratory.

- The prevailing (Durán Acevedo et al., 2021) didn't provide any stress management suggestions to the high-stressed students.
- The relationship between stress level and academic performance was not considered in existing techniques (Balamurugan et al., 2023).
- Owing to the high volume of different students' information, complexities occurred in stress level prediction.
- Most of the existing works didn't capture the temporal changes in stress levels.

1.2 Objectives

- Vital signs are taken from students while studying; then, the stress index is calculated by using A^2RQNFIS.
- Coping strategies are developed to provide stress management suggestions.
- PCC is utilized for correlation analysis, thereby analyzing the stress impact on academic performance.
- DB^{2}MSDHCAN is introduced to group the distinct student information.
- EGKF is used to capture the temporal changes in stress levels.

Thepaper is structured as: The existing works are described in Section 2, the proposed methodology is illustrated in Section 3, the result is conveyed in Section 4, and lastly, the proposed model is concluded in Section 5 with future scope.

2. LITERATURE SURVEY

(Durán Acevedo et al., 2021) offered a framework named Academic Stress Detection on university students. Here, to predict the stress level, the model employed K-Nearest Neighbors (KNN) and Support Vector Machine (SVM). Ahigh success rate was obtained in the research. But, this work didn't provide any stress management suggestions to the high-stress students.

(Balamurugan et al., 2023) discovered students' stress prediction model for academic growth. Here, to identify the mental stress of students, the Random Forest (RF) algorithm was used. Likewise, the model helped administrators to assess students' abilities. But, the research didn't consider the relationship between stress levels and academic performance.

(Nijhawan et al., 2022) presented a social interactions-based stress detection framework. Here, for stress detection, the ML approaches and Bidirectional Encoder Representation from Transformers (BERT) model were utilized. Ahigh detection rate was obtained by the model. But, this work had insufficient factors for stress analysis.

(Jiao et al., 2022) recommended a student academic performance prediction model in engineering education. Here, to predict the academic performance of engineering students, genetic programming was employed. The suggested model was better for evaluating the learning performance of students. But, it failed to capture the temporal changes of students for accurate prediction.

(Feng et al., 2022) offered an educational data mining-based students' academic performance prediction model. Here, for academic performance prediction, the Convolutional Neural Network (CNN)was utilized. Superior performance and high reliability were achieved in the research. However, this work had overfitting issues and a lack of generalizability.

3. PROPOSED METHODOLOGY

Here, to predict the stress level of engineering students, the proposed A^2RQNFIS is introduced. In Figure 1, the proposed model's diagrammatic representation is displayed.

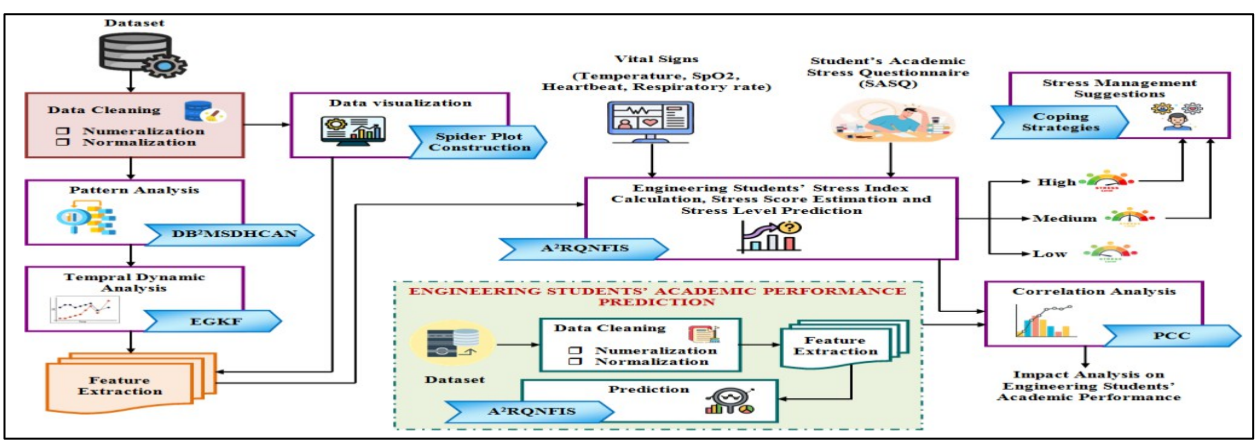


Figure 1: Diagrammatic representation of the proposed model

3.1 Dataset
Initially, to train the proposed model, the student's stress factor dataset is taken, and it is expressed as $\aleph_r^{data}$.

3.2 Data Cleaning
Next, to improve the data's quality, $\aleph_r^{data}$ are preprocessed. Initially, the string values in the $\aleph_r^{data}$ are converted into numerical values in the numeralization process and are signified as λ_∂. Then, by using min-max normalization, λ_∂ are normalized.

$$N(\lambda_\partial) = \frac{\lambda_\partial - min(\lambda_\partial)}{max(\lambda_\partial) - min(\lambda_\partial)} \tag{1}$$

Here, $\min(\lambda_\partial)$ and $\max(\lambda_\partial)$ specify the maximum and minimum values, respectively. The cleaned data is specified as $\wp_v$.

3.3 Pattern Analysis
Next, pattern analysis is performed based on the $\wp_v$ by using DB²MSDHCAN. Here, based on the similar patterns of students, $\wp_v$ is grouped. Density-Based Spatial Clustering of Applications with Noise (DBSCAN) allows for more flexible and accurate grouping. But, the important parameters in DBSCAN are epsilon and minpts, which need to be calculated accurately. Thus, the Bray-curtis Matusita distance and Dunn Hubert index are used in DBSCAN.
Primarily, the epsilon parameter (α) is estimated by employing Bray-curtis Matusita distance, which estimates the average similarity ratio of each cluster with its most similar cluster.

$$\alpha \to \sqrt{2\left(1 - \sum_v \sqrt{(\wp_v)(\wp_j)}\right)} * \frac{\sum_v |\wp_v - \wp_j|}{\sum_v |\wp_v + \wp_j|} \tag{2}$$

Here, j states the constant value. Then, the clusters are formed by minpts (γ), which is estimated by using Dunn Hubert index.

$$\gamma = \frac{\wp_{in} - \wp_{out}}{\sqrt{\wp_{in} + \wp_{out}}} * \frac{\min_{vj} D(\wp_v, \wp_j)}{\max_j dia(\wp_j)} \tag{3}$$

Where, $\wp_{in}$ and $\wp_{out}$ outline the data points in the same cluster and different clusters, respectively, D shows distance, and dia signifies diameter. Then, the core points (U) those aids in identifying the clusters is estimated.

$$U = \alpha \times \gamma \tag{4}$$

Based on the (U), (α), and (γ), the cleaned data are grouped according to similar patterns of students. This grouping is continued until convergence. The grouped data is represented as G_f.

Pseudocode for DB²MSDHCAN

Input: Cleaned data $(\wp_v)$

Output: Grouped data (G_f)

Begin

Initialize $(\wp_v)$

For each $(\wp_v)$

Estimate epsilon

$$\alpha \to \sqrt{2\left(1 - \sum_v \sqrt{(\wp_v)(\wp_j)}\right)} * \frac{\sum_v |\wp_v - \wp_j|}{\sum_v |\wp_v + \wp_j|}$$

Form clusters

$$\gamma = \frac{\wp_{in} - \wp_{out}}{\sqrt{\wp_{in} + \wp_{out}}} * \frac{\min_{vj} D(\wp_v, \wp_j)}{\max_j dia(\wp_j)}$$

Identify clusters by core points

$$U = \alpha \times \gamma$$

Continue until convergence

End For

Obtain (G_f)

End

Next, temporal dynamic analysis is done.

3.4 Temporal Dynamic Analysis

Then, by utilizing EGKF, the temporal dynamic analysis is performed centeredon G_f. Kalman Filter (KF) effectively provides timely updates. Also, poor initialization can lead to slow convergence in KF. Thus, in KF, the ErlangGompertz function is used.Initially, by using the ErlangGompertz function (ξ), the state estimate (Y_{st}) and the state estimate (Y_{st}) and covariance estimate (Z_{co}) are initialized.

$$\xi = v \exp^{-w \exp^{-xG_f}} * \frac{(vG_f)^{w-1} \exp^{-vG_f}}{(w-1)!} \tag{5}$$

Here, v, w, and x are the constants. Next, expected measurement $(\tilde{J}_{\bar{p}})$ and measurement residual (B_p) are predicted as,

$$\tilde{J}_{\bar{p}} = Q_p \tilde{Y}_{\bar{p}} \tag{6}$$

$$B_p = J_p - \tilde{J}_{\bar{p}} \tag{7}$$

Here, Qp implies the measurement matrix, Yp indicates the predicted state estimate, and $\tilde{J}$ p signifies the new measurement. Next, Kalman gain Ka p~ is calculated. Similarly, the state estimate and covariance matrix are updated based on (B_p), which are denoted as Yp and Z p , respectively. Similarly, for the next step, the state and covariance matrix are predicted, which are represented as $\tilde{Y}_{\bar{p}+1}$ and $\tilde{Z}_{\bar{p}+1}$, correspondingly. Finally, the temporal dynamic analysis outcomes are signified as T_u.

Pseudocode for EGKF

Input: Grouped data (G_f)

Output: Temporal dynamic analysis outcomes (T_u)

Begin

Initialize (G_f)

For each (G_f)

Initialize (Y_{st}) and (Z_{co}) using (ξ)

$$\xi = v \exp^{-w \exp^{-xG_f}} * \frac{(vG_f)^{w-1} \exp^{-vG_f}}{(w-1)!}$$

Predict $\tilde{J}_{\bar{p}} = Q_p \tilde{Y}_{\bar{p}}$

$$B_p = J_p - \tilde{J}_{\bar{p}}$$

Estimate kalman gain (Ka_p)

Update (Y_{st}) and (Z_{co})

Compute next step $\tilde{Y}_{\bar{p}+1}$ and $\tilde{Z}_{\bar{p}+1}$

End For

Obtain $(\mathcal{F}_u)$

End

Then, features are extracted from $\mathcal{F}_u$.

3.5 Data Visualization

Likewise, the data visualization is done from $\wp_v$. Here, to visualize the distinct student information without any overlap, the spider plot is constructed and is defined as V_{plot}.

3.6 Feature Extraction

Then, from V_{plot}, features, such as Academic Pressure, Sleep Quality, Extracurricular Involvement, and Self-Efficacy are extracted, and it is indicated as F_υ. Similarly, from $\mathcal{F}_u$, the features, such as academic milestones, stress variability, and exam preparation time are extracted, and it is signified as χ_a. The extracted features are considered as E_κ.

3.7 Engineering Students' Stress Index Calculation, Stress Score Estimation, and Stress Level Prediction

Next, by employing A2RQNFIS, engineering students' stress index calculation, stress score estimation, and stress level prediction are performed. Adaptive Neuro-Fuzzy Inference System (ANFIS) effectively adjust sits parameters based on new data or changes. Still, ANFIS often requires appropriate membership functions and rule bases. Thus, in ANFIS, the Arctangent Rational Quadratic membership function is employed.

3.7.1 Vital Signs-based Stress Index Calculation

Here, the vital signs, such as temperature, peripheral oxygen saturation (SpO2), heartbeat, and respiratory rate are taken from students while studying through the wearable devices. Next, the stress index (Ω) is calculated based on the vital signs.

$$\Psi = \begin{cases} if\ t > 36\ \ \&\&\ \ s > 0.95\ \ \&\&\ \ h > 60\ \ \&\&\ \ R > 12 & low \\ if\ t = 36 - 37.5\ \ \&\&\ \ s = 0.95 - 1\ \ \&\&\ \ h = 60 - 100\ \ \&\&\ \ R = 12 - 20 & medium \\ if\ t < 37.5\ \ \&\&\ \ s < 1\ \ \&\&\ \ h < 100\ \ \&\&\ \ R < 20 & high \end{cases} \tag{8}$$

Where, Ψ indicates the vital sign ranges.

$$\Omega \xrightarrow{\Psi} \begin{cases} if\ t == low \,\&\&\, s == low \,\&\&\, h == low \,\&\&\, R == low & \Omega = low \\ if\ t == low \,\&\&\, s == medium \,\&\&\, h == low \,\&\&\, R == low & \Omega = low \\ if\ t == high \,\&\&\, s == high \,\&\&\, h == low \,\&\&\, R == high & \Omega = medium \\ if\ t == high \,\&\&\, s == high \,\&\&\, h == medium \,\&\&\, R == medium & \Omega = medium \\ if\ t == medium \,\&\&\, s == high \,\&\&\, h == high \,\&\&\, R == high & \Omega = high \\ if\ t == high \,\&\&\, s == high \,\&\&\, h == high \,\&\&\, R == medium & \Omega = high \\ \vdots & \vdots \\ if\ t == high \,\&\&\, s == high \,\&\&\, h == high \,\&\&\, R == high & \Omega = high \end{cases} \tag{9}$$

Where, t implies temperature, s illustrates SpO2, h denotes heartbeat, and R indicates respiratory rate.

3.7.2 SASQ-based Stress Score Estimation

Similarly, SASQ is considered; from that response, the stress score is estimated. For each questionnaire, the options like never-0, almost never-1, sometimes-2, fairly often-3, and very often-4 are considered. The values (i.e.,0 means 4, 1 means 3, 2 means 2, 3 means 1, and 4 means 0) are assigned to the options. Then, to calculate the stress score (Θ), the obtained values from the students for each questionnaire are added.

$$\Theta = \begin{cases} if \quad \delta == (0-13) & low\ stress \\ if \quad \delta == (14-26) & medium\ stress \\ if \quad \delta == (27-40) & high\ stress \end{cases} \tag{10}$$

Where, (δ) is the added value.

3.7.3 Stress Level Prediction

Finally, the stress level is predicted based on the E_κ, Ω, and Θ by using A²RQNFIS. The inputs E_κ, Ω, and Θ are considered as μ_ϕ .In Figure 2, the A²RQNFIS diagram is shown.

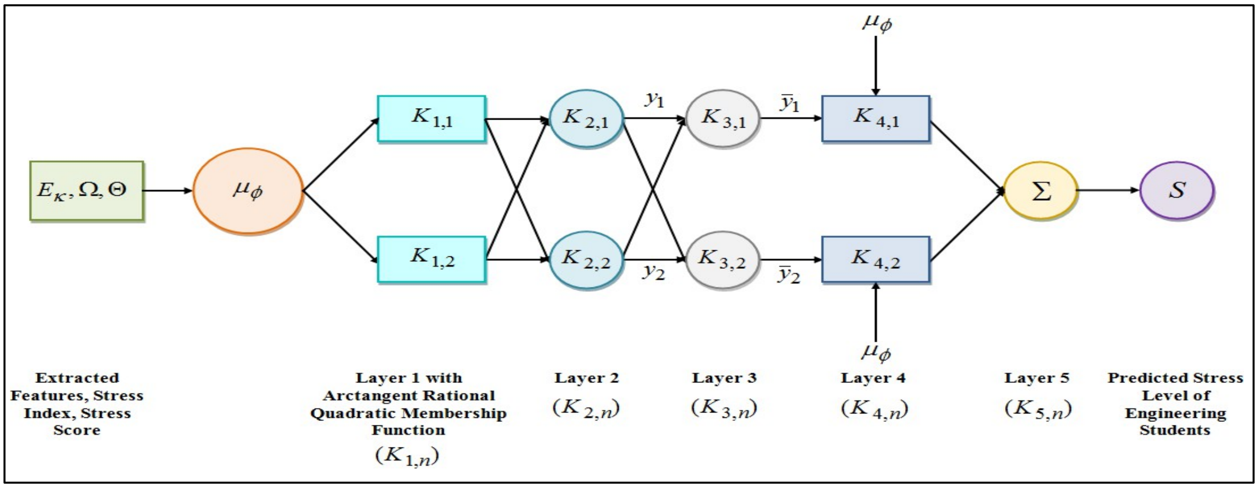


Figure 2: A²RQNFIS diagram

Fuzzification layer: Initially, each node is adjusted to a function parameter, and the membership function is the output of each node. The fuzzification layer $(K_{1,n})$ is given as,

$$K_{1,n} = \beta(\mu_\phi) \tag{11}$$

Here, β indicates the Arctangent Rational Quadratic membership function, and it is expressed as,

$$\beta(\mu_\phi) = \frac{1}{\pi} arc\left(l\left(\mu_\phi - C\right)\right) + \frac{1}{2\left(1 + \left(\frac{\mu_\phi - C}{d}\right)^2\right)} \tag{12}$$

Here, arc notates the arctangent function, l indicates steepness, C exemplifies the center, and d signifies the spread.

Rule layer: Here, each nodes are fixed. Similarly, firing strength is calculated for each rule. The rule layer $(K_{2,n})$ is estimated as,

$$K_{2,n} = y_n = \beta(\mu_\phi) \quad where \quad n = 1,2 \tag{13}$$

Where, y_n indicates the firing strength.

Normalization layer: In the normalization layer, the firing strength is normalized as follows,

$$K_{3,n} = \bar{y}_n = \frac{y_n}{\sum_n y_n} \tag{14}$$

Here, $\bar{y}_n$ signifies normalized firing strengths.

Defuzzification layer: Then, in the defuzzification layer $(K_{4,n})$, each node possesses a node function, and it is determined as,

$$K_{4,n} = \bar{y}_n \cdot (\Omega, \Theta) = y_n\left(\varepsilon_n \mu_\phi + k_n\right) \tag{15}$$

Where, ε_n and k_n signify the parameter set.

Output layer: The final output is discovered by estimating the whole addition of all the arriving signals from the previous node. The output layer $(K_{5,n})$ is formulated as,

$$K_{5,n} = \sum_n \overline{y}_n \cdot (\Omega, \Theta) = \frac{\sum_n \overline{y}_n \cdot (\Omega, \Theta)}{\sum_n \overline{y}_n} \tag{16}$$

Ultimately, the predicted stress level of engineering students (S) is given as,

$$S = \langle H, M, L \rangle \tag{17}$$

Here, H indicates high stress, M depicts medium stress, and L shows low stress.

3.8 Stress Management Suggestions

If the stress level is high (H) and medium (M), then coping strategies-based stress management suggestions are provided to the students. Coping strategies are a set of suggestions that are used to tolerate and reduce stress events.

3.9 Engineering Students' Academic Performance Prediction System

Similarly, engineering students' academic performance prediction system is trained as follows,

3.9.1 Dataset

Primarily, to train the prediction model, thestudent academic performance dataset is taken, and it is defined as ϑ_m^{data}.

3.9.2 Data Cleaning

Then, based on numeralization and normalization, ϑ_m^{data} is pre-processed. Here, the cleaned data is indicated as Φ_e.

3.9.3 Feature Extraction

Next, from Φ_e, the features, such as StudentAbsenceDays, GradeID, SectionID, and Discussion are extracted and are represented as $\hat{\lambda}_z$.

3.9.4 Prediction

Next, by using A^{2}RQNFIS, the engineering students' academic performance is predicted based on $\hat{\lambda}_z$. In Section 3.7, the steps involved in A^{2}RQNFIS are explained. The predicted academic performance (P) is written as,

$$P = \langle \hbar, \varpi, \ell \rangle \tag{18}$$

Where, $\hbar$, ϖ, and ℓ show the high, medium, and low performances, respectively.

3.10 Correlation Analysis

Then, the correlation analysis is done between the predicted stress level variables (S_g) and academic performance variables (P_i) based on the (S) and (P) by using PCC.

$$Cor = \frac{\sum (S_1 - \overline{S}_1)(P_1 - \overline{P}_1)}{\sqrt{\sum (S_1 - \overline{S}_1)^2 (P_1 - \overline{P}_1)^2}} \tag{19}$$

Here, Cor notates the correlation value, $\overline{S}_1$ depicts the mean of S_1, and $\overline{P}_1$ implies the mean of P_1. Likewise, Cor is identified for all (S_g) and (P_i).

3.11 Impact Analysis on Academic Performance

Lastly, based on Cor, impact analysis (I_A) is performed.

$$I_A = \begin{cases} if \quad Cor == high \quad high - impact \\ if \quad Cor == low \quad less - impact \end{cases} \tag{20}$$

Therefore, the proposed model proficiently predicted the stress level of engineering students and analyzed its impacts.

4. RESULT AND DISCUSSION

Here, the proposed model's performance assessment is done to prove its trustworthiness. The proposed model is implemented in the working platform of PYTHON.

4.1 Dataset Description

To assess the proposed model, the student's stress factor dataset and student academic performance dataset are used. In the reference section, the dataset link is mentioned. Here, the student's stress factor dataset consists of 1100 students' stress factor information. Similarly, the student academic performance datasetcontains 480 number of students' academic performance information. From that, 80% of data are employed for training and 20% of data are utilized for testing.

4.2 Performance Validation

Here, the performance validation of the proposed model and prevailing techniquesis done.

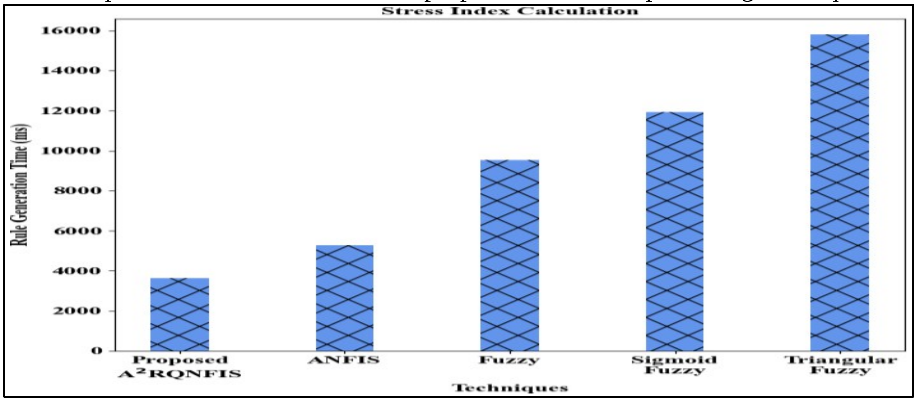


Figure 3: Rule generation time analysis

The rule generation time analysis of the proposed model is displayed in Figure 3. For rule generation time, the proposed A^2RQNFIS obtained a low value of 3624ms, whereas the existing techniques like ANFIS, Fuzzy, Sigmoid Fuzzy, and Triangular Fuzzy attained high values.

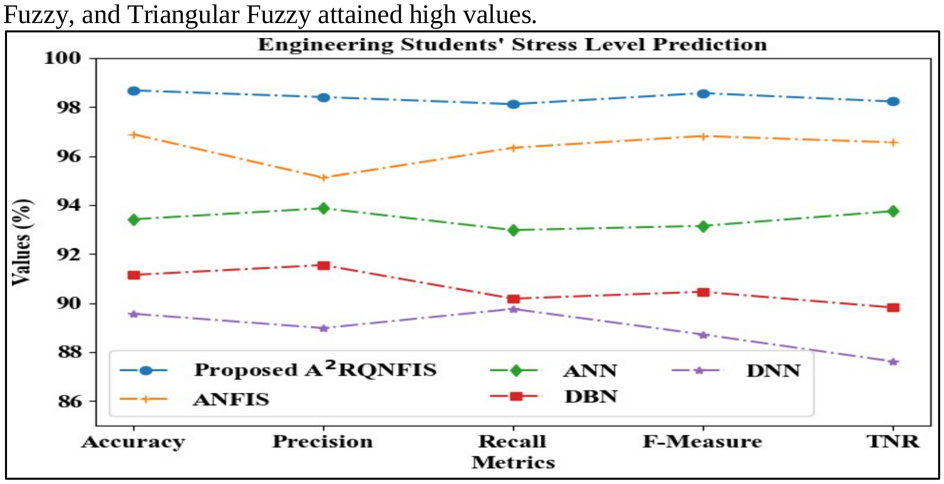


Figure 4: Performance estimation based on performance metrics

In Figure 4, the performance estimation based on performance metrics is shown. For accuracy, precision, recall, F-measure, and True Negative Rate (TNR), the proposed A^2RQNFIS achieved high percentages of 98.68%, 98.41%, 98.12%, 98.57%, and 98.23%, respectively, while the prevailing techniques like ANFIS, Artificial Neural Network (ANN), Deep Belief Network (DBN), and Deep Neural Network (DNN) attained low-performance metrics.

Table 1: Comparative assessment

Techniques	**Training time (ms)**
Proposed A^2RQNFIS	35724
ANFIS	45914
ANN	75149
DBN	95743
DNN	113912

Table 1 shows the comparative evaluation of the proposed A^2RQNFIS with the conventional methods. For training, the A^2RQNFIS took a less time of 35724ms, whereas the prevailing methods took a high time of 82679.5ms.

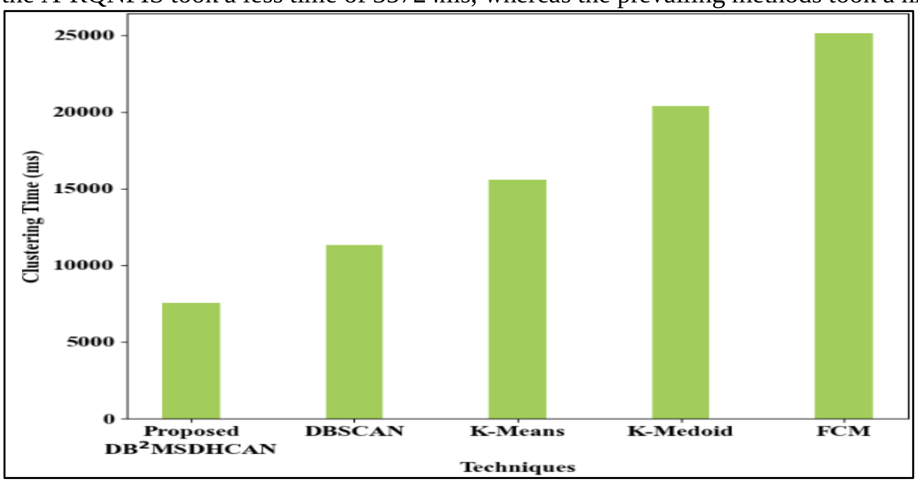


Figure 5: Clustering time validation

Figure 5 analogizes the proposed model with the existing techniques regarding clustering time. The DB^2MSDHCAN attained a low clustering timeof 7562ms. But, the existing methods attained a high clustering time of 18095.25ms.

Table 2: Performance estimation

Techniques	**Silhouette score**
Proposed DB^2MSDHCAN	0.982
DBSCAN	0.965
K-Means	0.937
K-Medoid	0.908
FCM	0.883

Table 2 shows the performance estimation regarding silhouette score. Here, the proposed DB^2MSDHCAN achieved a high silhouette score of 0.982, whereas the prevailing methods, such as DBSCAN, K-Means, K-Medoid, and Fuzzy C-Means (FCM) attained low silhouette scores.

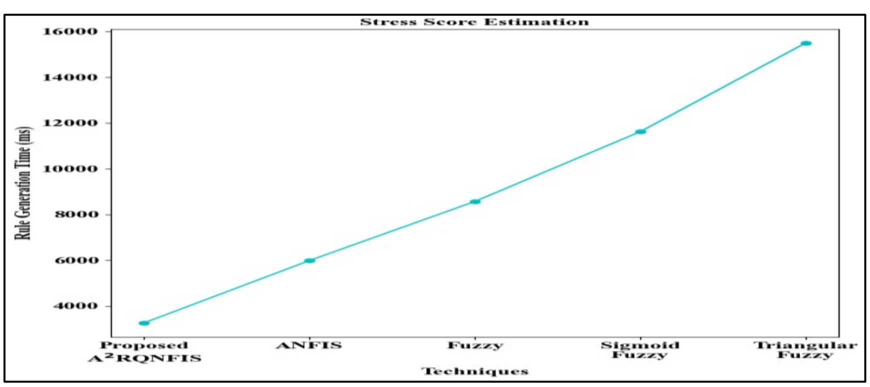


Figure 6: Graphical analysis of rule generation time

The graphical analysis of rule generation time is displayed in Figure 6. For stress score estimation, the proposed A^2RQNFIS obtained a low rule generation time of 3256ms; yet, the prevailing methods attained high rule generation times.

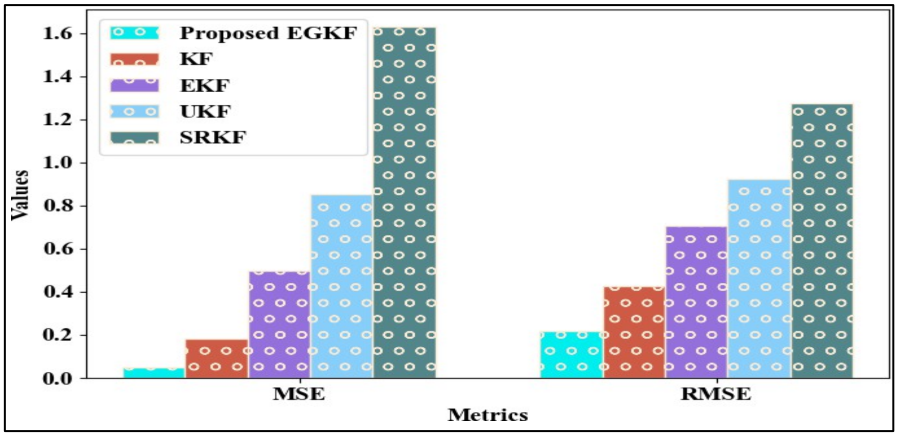
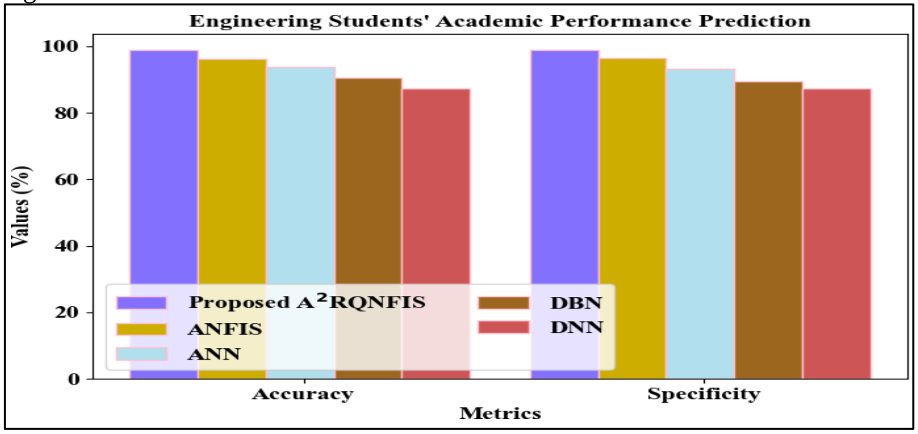
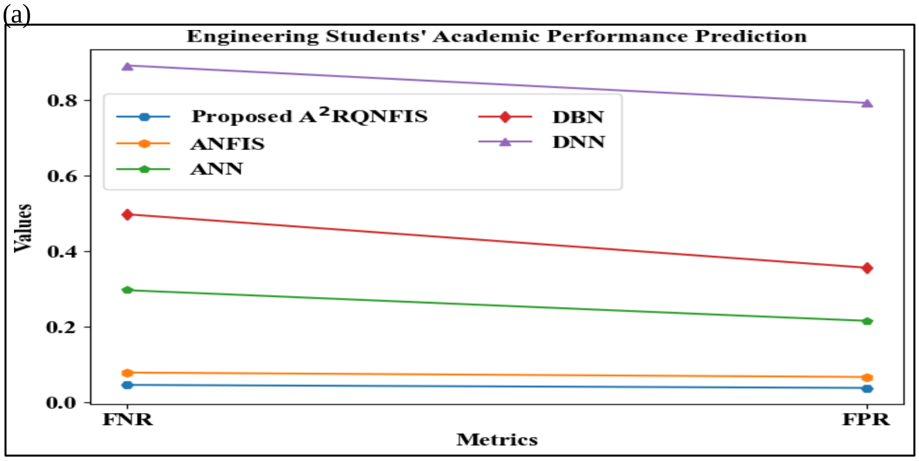


Figure 7: Comparative assessment of the proposed model

In Figure 7, the proposed model is weighed against the prevailing techniques. The proposed EGKF achieved a low Mean Squared Error (MSE) and Root Mean Square Error (RMSE) of 0.0467 and 0.2161, whereas the conventional KF, Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and Square Root Kalman Filter (SRKF) attained high error values.



(a)



(b)

Figure 8: Graphical representation regarding (a) Accuracy, Specificity (b) FNR, FPR

The graphical representation of the proposed A^2RQNFIS and prevailing methods is depicted in Figure 8. For accuracy and specificity, the proposed A^2RQNFIS obtained a high percentage of 98.78% and 98.77%, respectively. Similarly, with the help of the Arctangent Rational Quadratic membership function, the proposed A^2RQNFIS attained a low False Negative Rate (FNR) and False Positive Rate (FPR). But, poor performance metrics were attained by the prevailing methods like ANFIS, ANN, DBN, and DNN.

4.3 Comparative Analysis

Here, the comparative analysis of the proposed model and related works is performed.

Table 3: Comparative analysis

Authors' name	Techniques	Accuracy (%)	Precision (%)	F-measure (%)
Proposed model	A^2RQNFIS	98.68	98.41	98.57
(Walambe et al., 2021)	ANN	96.67	95	95
(R. V. Anand et al., 2023)	Ensemble learning	93.48	-	93.14
(Du, 2022)	XGBoost	77.5	-	-
(Chen & Lee, 2023)	Self-supervised CNN	93.42	-	88.11
(Anand et al., 2024)	CNN	87.63	-	-

The proposed model is weighed against the related works in Table 3. For accuracy, precision, and F-measure, the proposed model achieved a high percentage of 98.68%, 98.41%, and 98.57%, respectively. Similarly, the existing ANN, Ensemble learning, eXtreme Gradient Boosting (XGBoost), self-supervised CNN, and CNN obtained poor performance in predicting the stress level of engineering students.

5. CONCLUSION

Here, vital signs-based engineering students' stress level prediction and impact analysis on academic performance using A^2RQNFIS are presented. To assess the proposed model, the Student Stress Factor dataset was employed. For stress level prediction, a high accuracyof 98.68% was attained by the proposed A^2RQNFIS. Similarly, a low clustering time of 7562ms was attained by the proposed DB^2MSDHCAN. Overall, the proposed framework had superior efficiency and low time complexity. However, the model only predicted the present stress level of students. Moreover, it failed to focus on the long-term impact analysis of stress in students. This highlighted a significant problem in understanding the long-term consequences of chronic stress on young individuals' lives. Also, the proposed model didn't provide deeper insights into how sustained stress influenced cognitive abilities, learning processes, decision-making, and professional growth over time.

Future Scope

Improved techniques will be developed in the future to analyze how chronic stress affects academic performance and long-term career outcomes. These improved approaches will likely integrate innovative tools like longitudinal studies, advanced statistical modeling, and AI to offer deeper insights into chronic stress.

We have no conflicts of interest to disclose.All authors declare that they have no conflicts of interest.

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