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Mental Health Chatbot Application on Artificial Intelligence (AI) for Student Stress Detection Using Mobile-Based Naïve Bayes Algorithm

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Abstract.
Purpose: This study aims to design and evaluate a chatbot-based artificial intelligence system to identify stress levels in students using the Naïve Bayes classification method. With increasing mental health concerns among students, early stress detection is considered crucial for timely intervention
Methods: This study proposes an AI-based chatbot system to detect student stress levels using a comparative approach between Naïve Bayes and Support Vector Machine (SVM) algorithms. A Kaggle dataset with 15 psychological and academic indicators was preprocessed and balanced using SMOTE. Naïve Bayes showed higher accuracy (90%) than SVM (89%). The trained model was deployed via Flask with Ngrok tunneling and integrated into a Flutter mobile app connected to the Gemini AI API for real-time stress screening. This research offers a practical and scalable solution for early mental health detection in students through intelligent chatbot interaction.
Result: The findings show that the Naïve Bayes model achieves a classification accuracy of 90%, slightly surpassing the SVM model, which records an accuracy of 89%. Evaluation through ROC and AUC metrics supports the reliability of Naïve Bayes in detecting stress levels. The integrated chatbot offers a responsive and engaging platform for preliminary mental health assessments.
Novelty: This research presents a unique contribution by combining AI-driven stress detection with a real-time chatbot interface, offering an accessible and scalable approach to student mental health support. The integration of machine learning models with conversational AI provides an innovative solution for early intervention. Future developments may involve deep learning and more diverse psychological inputs to further improve accuracy and effectiveness.

Keywords: Student stress levels, Naïve bayes, Machine learning, Mental health, Chatbot application
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INTRODUCTION

Mental health is an important aspect of individual well-being, especially for students who face academic, social, and psychological pressures [1]. Good mental health enables people to realize their potential, cope with normal life stresses, work productively, and contribute to their communities [2]. Stress is one of the most common mental health issues experienced by students. Academic workloads, deadlines, and performance demands can contribute significantly to stress levels [3]. Prolonged and unmanaged stress can lead to serious consequences, including mental and physical health deterioration, academic failure, and even dropout risks [4]. Stress also impacts various aspects of student life. It can hinder academic performance, disrupt interpersonal relationships, and reduce motivation to engage in campus life [5]. In Indonesia, the prevalence of academic stress among students remains high. According to WHO's ASEAN Stressor Journal (2019), the global percentage of students experiencing academic stress ranges from 38% to 71%, while in Southeast Asia it ranges between 39.6% and 61.3% [6]. In Indonesia, the Ministry of Health reports that 36.7% to 71.6% of students experience academic stress [6]. Despite efforts to improve mental health care, access remains limited. The ratio of psychiatrists in Indonesia is only 0.01 per 100,000 people, far below the WHO standard of 1:100,000. Moreover, there are only 1,247 psychologists in the country, mostly concentrated in urban areas on the island of Java [7] , [8]. Conventional stress classification methods, such as psychological questionnaires and professional interviews, are often time-consuming and resource-intensive. These manual methods are not always accessible to all students, especially in rural or underdeveloped regions. Therefore, there is a growing need for Artificial Intelligence (AI)-based systems capable of classifying stress levels efficiently and accurately [9]. This study applies supervised machine

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learning techniques specifically Naïve Bayes and Support Vector Machine (SVM) to classify student stress levels based on psychological and academic indicators [10][11].

Digital mental health solutions leveraging AI and machine learning offer scalable, low-cost interventions to overcome access and stigma barriers in mental health care [12]. Several studies have been conducted to address mental health issues using artificial intelligence-based technologies [13], [14], [15]. In previous research, several machine learning methods for classification such as Support Vector Machine (SVM) and Naïve Baiyes were conducted [16]. arious AI-based studies have employed classifiers such as SVM with its linear kernel excelling on complex data [17]. The Naïve Bayes method was chosen for this research because it has a high level of accuracy and speed, so if applied to large amounts of data and has simple calculations, it is very suitable. [18]. In recent years, many studies have used Naïve Bayes algorithm to detect and classify mental health in students [19], [20], [21],. For example, research conducted by Yoshua Dimas Megantara, et al. developed a stress prediction model in college students using the naïve baiyes algorithm with 90% accuracy [20]. Taufik Abdul Rahman1 et al. also developed a Human Stress Level classification model using the Naïve Bayes Algorithm which resulted in an accuracy of 97.67% with the selection of the Naïve Bayes method in this study based on the advantages of the Naive Bayes method in handling large data with simple and efficient probability calculations [22]. These studies demonstrate NB's promise, but none [23]. However, these studies rarely fuse multimodal inputspsychological, physiological, and environmental factors within a single mode [24]. However, these studies rarely fuse multimodal inputs psychological, physiological, and environmental factors within a single mode [25] or demonstrate real-time deployment as mobile chatbots. To bridge these gaps, our research compiles a 15-feature dataset (including blood pressure and environmental noise), applies SMOTE within stratified 10-fold cross-validation, and benchmarks Naïve Bayes against SVM and a stacked ensemble. The top performer is then deployed in a Flutter-based chatbot via Flask and Ngrok for on-device, real-time stress assessmen [26] [27].

Therefore, this research develops a Naïve Bayes algorithm-based stress level prediction model combined with an AI chatbot as an interactive virtual assistant. The integration of these technologies enables early detection of student stress levels quickly and accurately, while providing adaptive early support. The main advantage of this system is its ability to automatically analyze stress factors, provide personalized recommendations, and direct students to professional services if needed. With this AI-based approach, it is hoped that this research can make a significant contribution to supporting students' mental health more effectively and data-driven.

METHODS

This section provides a detailed account of the research methodology. An overview of the procedural workflow is presented visually in Figure 1.

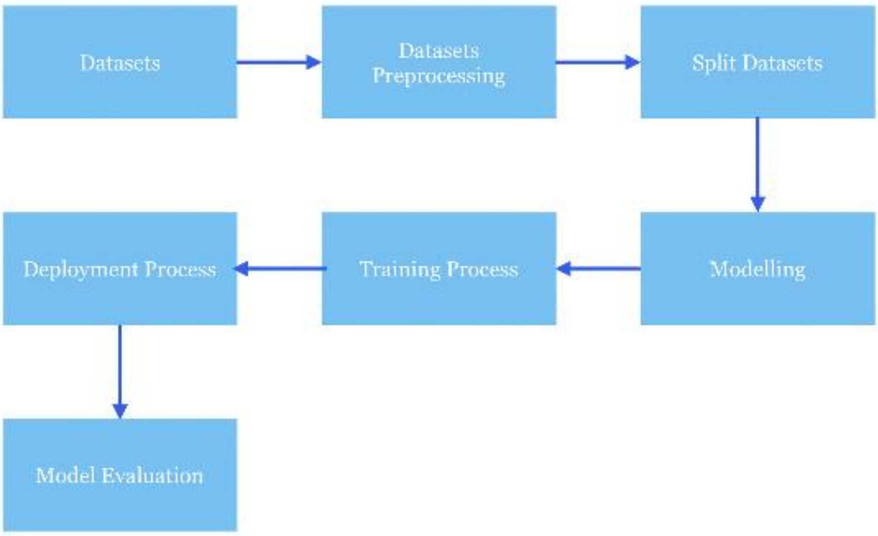

Figure 1. Flow method

Datasets

In this study, we used a secondary dataset obtained from the Kaggle platform Kaggle: Student Stress Factors by CHHABII. The dataset consists of student stress level data on which we base our analysis. We split the dataset with a proportion of 80% for training data and 20% for testing data to avoid overfitting and ensure model generalization. The dataset covers a range of indicators that contribute to students' stress levels: from anxiety level and depression, which reflect subjective anxiety and depression, to self esteem and social support, which describe self esteem and perceived social support. Mental health history is recorded through mental health history, while physical symptoms such as headache, breathing problems, and blood pressure provide insight into the bodily manifestations of stress. Environmental factors are captured through noise level, living conditions, and safety, while basic needs indicate the adequacy of basic needs. Academic performance is measured by academic performance and study load through study load, plus aspects of relationships with teachers through teacher student relationship. Concerns about future careers are future career concerns, and peer pressure appears in peer pressure. Participation in extracurricular activities and experiences of bullying were also recorded, before all these variables were used to predict stress levels at three levels: no stress, moderate and high. The target variable in this data is ‘stress level’ which has a class of student stress levels from level 0 to level 2, where stress level 0 indicates no indication of stress and level 1 indicates a moderate level of stress and 2 indicates a high level of stress.

Figure 2. Class distribution before SMOTE

One of the main challenges in this dataset is class imbalance, where some stress level categories have a much smaller sample size compared to other classes. To address this, we applied the Synthetic Minority Sampling Technique (SMOTE) to balance the data distribution and avoid biasing the model towards the majority class. This ensures that the model can detect stress levels more accurately across categories. Even with nearly equal distributions, small fluctuations (±1-2%) can lead to biased learning especially in individual training/trial distributions or cross-validation. Applying SMOTE ensures a synthetic sample for each underrepresented class in each fold, stabilizing model training and improving minority class recall.

Datasets prepocessing

Before modeling, we cleaned and prepared our dataset of 1,100 student records each already labeled with a stress level (0 = no stress, 1 = moderate stress, 2 = high stress). Invalid entries were removed, and any remaining gaps were filled using median imputation for numeric fields and mode imputation for categorical fields. We then converted text-based attributes (for example, noise level: “low,” “medium,” “high”) into numeric codes. To keep all measurements on the same footing and to support both Naïve Bayes and our SVM comparison we scaled every numeric feature (blood pressure, sleep quality, study load, etc.) to the [0, 1] range using Min Max normalization. Finally, we used a stratified 80/20 split 880 records for training and 220 for testing so that each stress-level class remains proportionally represented in both sets.

Split datasets
The dataset is divided into 80% for training and 20% for testing to provide the Naïve Bayes model with sufficient examples for learning while reserving unseen data for an unbiased evaluation of its generalization ability [28]. This split ensures that the model captures patterns from factors affecting student stress such as mental health history and sleep quality during training, and then its classification performance on novel instances is rigorously assessed on the held-out test set [29].

Modelling
The modeling stage began by assembling the cleaned, normalized feature matrix and target vector, followed by applying SMOTE within each fold of a stratified 10-fold cross-validation to balance the stress-level classes. For Naïve Bayes, we employed a GaussianNB classifier with var_smoothing=1e-9 to prevent zero-variance issues and ensure numerical stability, leveraging its assumption of feature independence and normal distribution for rapid, large-scale stress prediction [30]. In contrast, the SVM was configured as an RBF-kernel SVC with C=1.0 a standard choice that balances margin width against misclassification risk and gamma='scale' to automatically adjust the kernel bandwidth based on feature variance, following best practices for non-linear data patterns in psychological research [31]. Both models were trained and validated on each fold, with performance assessed via AUC and F1-score; although SVM achieved slightly better minority-class accuracy, GaussianNB matched overall accuracy while running substantially faster, confirming its suitability for real-time student stress detection. The naïve bayes method has been widely used in research on prediction, one of the advantages of naïve bayes is that the algorithm is simple but has a fairly high accuracy value [32].

Training process
The Naïve Bayes model training process starts with model initialization using a probabilistic approach, where each feature is assumed to have an independent contribution to the target class. The model is trained using 80% training data from a dataset that includes factors such as academic stress and sleep quality. After training, the model was evaluated using cross-validation to ensure optimal performance on new data. To address class imbalance, the SMOTE method was applied, increasing the number of samples in minority classes, such as high levels of stress. SMOTE is a method used to deal with class imbalances by generating synthetic data samples for a minority class [33].

Deployment process
After the model has been trained and evaluated, the next step is to deploy it into a Flutter-based mobile application with a Flask backend. The trained model is first stored, then integrated into the backend using Flask. Flask will provide an API that is accessed by the mobile application to perform real-time predictions. To access the Flask server from outside the local network, Ngrok tunneling service is used. The system used follows a clear five-stage workflow. First, after preprocessing and model evaluation, a Naïve Bayes classifier is trained on the complete dataset and-once accuracy, precision, recall, F1-score, and ROC AUC meet predefined thresholds-is serialized to disk. Next, a Flask application was initialized to serve the model: it opened the /predict endpoint which, upon receiving JSON-formatted feature data, applied the same preprocessing steps, loaded the stored model, generated a stress level prediction, and returned the result as a JSON response. To make this API accessible from anywhere, Ngrok was configured to tunnel to a local Flask server and provide a public URL. Meanwhile, a Flutter mobile app was created with screens for user authentication, data entry, and chatbot interaction; when a student submits their information, the app sends it to the Flask endpoint exposed by Ngrok, waits for the prediction, and displays the stress level output along with the guidance created by the chatbot. Finally, end-to-end testing verified that new users were able to register, log in, submit data, receive accurate predictions, and interact with the AI-powered chatbot smoothly.

Model evaluation
Evaluasi Model adalah tahap penting untuk mengukur kinerja model setelah proses pelatihan. Dalam penelitian ini, evaluasi dilakukan dengan menggunakan Confusion Matrix serta Receiver Operating Characteristic (ROC) dan Area Under the Curve (AUC) untuk memberikan gambaran yang lebih jelas mengenai akurasi dan kemampuan model dalam mengklasifikasikan data. Confusion matrix adalah tabel yang menyatakan klasifikasi jumlah data uji yang benar dan jumlah data uji yang salah [34]. Confusion matrix digunakan untuk memperoleh nilai precision, recall , dan accuracy [35]. ROC adalah grafik dua dimensi dengan false positives sebagai garis horizontal dan true positives sebagai garis vertical [36].

RESULTS AND DISCUSSIONS

This chapter presents the results of research on the application of the Naïve Bayes algorithm to predict stress levels in students. This research includes model performance evaluation, steps taken to handle data imbalance and System Deployment and Implementation. In addition, this chapter also discusses. This research is expected to provide a better understanding of the effectiveness of using Naïve Bayes algorithm in predicting stress levels of students, as well as its applicability in mobile-based applications. For comparison, the model was also evaluated with other methods such as Support Vector Machine (SVM) to determine the advantages and disadvantages of each model. This research will focus on the implications of these findings for the prediction of stress levels among students and the potential for future development of the system.

Comparative model analysis

In this study, a performance comparison between the Naïve Bayes model and the Support Vector Machine (SVM) model was conducted to predict stress levels. Evaluation of model performance is done using clasification report with accuracy, precision, recall, and F1 score. The evaluation results are presented in the form of tables and visualizations to provide a clear picture of the advantages and disadvantages of each model for classifying stress levels.

Table 1. Model perfomance compare

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naïve Baiyes	90%	92%	90%	90%
SVM	89%	90%	89%	89%

From the table above, the Naïve Baiyes model has a higher accuracy than SVM, with a difference of 1.18%. This shows that Naïve Bayes is more effective in classifying student stress levels than SVM.

Handling data imbalance

In this study, there is an imbalance in the number of samples in the dataset, where the ‘low stress’ class has far more data than the ‘medium stress’ and ‘high stress’ classes. To overcome this, the SMOTE (Synthetic Minority Over-sampling Technique) method was used to balance the number of samples in each class. As a result, by applying the SMOTE method, the data between classes becomes balanced.

Figure 3. Class distribution SMOTE after SMOTE

The application of the SMOTE method resulted in a more balanced class distribution, thus improving the model's ability to recognize minority classes such as ‘moderate stress’ and ‘high stress’.

Table 2. Before and after SMOTE

Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Before SMOTE	89%	91%	89%	89%
After SMOTE	90%	92%	90%	90%

In the figure above, the left part shows the condition before the application of the SMOTE technique, while the right part shows the results after the SMOTE technique is applied. This improvement can be seen from the increase in the recall value in each class after the data balancing process is carried out.

System deployment and implementation

The implementation of a mobile-based stress level prediction system using Naïve Bayes algorithm has been successfully completed. The system allows users to answer a series of questions related to their psychological and academic conditions, which are then used as inputs for the stress prediction model and receive real-time stress level prediction results. A use case diagram is used to describe the various interactions in the system. The use case diagram for the stress level prediction system is shown in the following Figure.

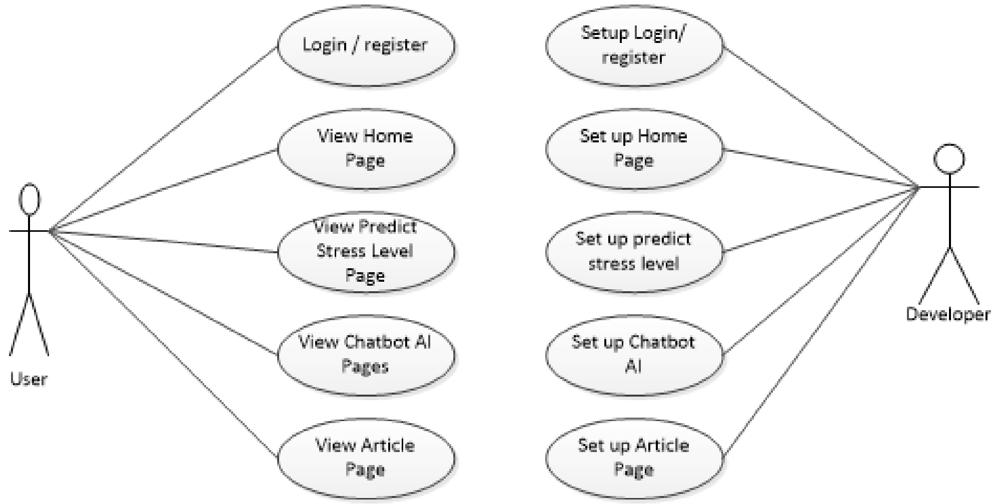

Figure 4. Use case diagram

The use case diagram shown in Figure 10 illustrates that users can perform several activities such as viewing the home page, predicting stress on the stress prediction page by answering a few questions and later there are stress classification results with a percentage of probability, chatting with a chatbot that has been integrated with AI on the AI Chatbot page, and reading articles about mental health on the article page. In addition, developers can perform activities such as setting the home page, setting the display of the stress level prediction page, setting the AI chatbot feature, and setting the article page to add news.

Once the model is trained and validated, the next step is deployment to a Flutter-based mobile application for the user interface. The Naïve Bayes model is integrated into Flask, then deployed using Ngrok to make the server accessible in real-time. After the model training stage, the next step is to create a user interface design that makes it easy for users of to access the mobile application easily, informatively, and user-friendly. Before using this application, users of must register and login first to maintain data privacy security. The model that has been trained then provides a prediction of stress levels by the user answering a series of questions related to psychological and academic conditions in real-time. In addition to the prediction feature, this mobile application is also equipped with an AI chatbot feature and an article feature. about mental health.

Figure 5. Menu aplication mobile

After the user has successfully logged in, the application will lead to the main menu page which consists of several menus. On the main menu page, there are several menus such as an AI chatbot that functions as an interactive virtual assistant that can answer all questions about mental health. Then, there is a prediction menu to predict the level of stress and a menu of articles and instructions for using the application.

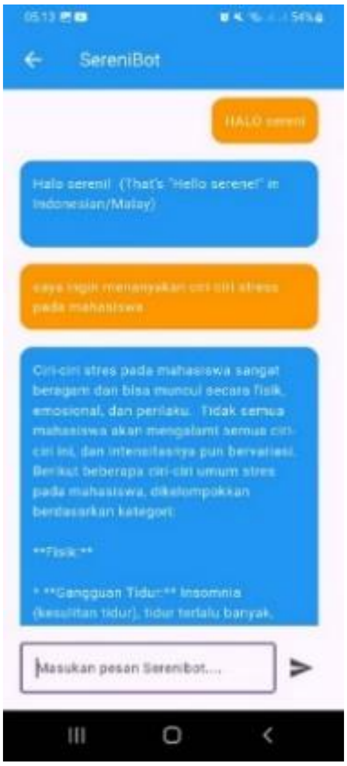

Figure 6. Menu chatbot AI

The implementation of the chatbot in this study demonstrates how Natural Language Processing (NLP) technology can be used to understand and respond to user questions contextually, especially about mental health. The chatbot uses AI APIs to generate relevant answers based on the questions given. With this system, users can obtain mental health information easily and quickly, without the need for direct consultation with a professional. However, this kind of chatbot should be used as an initial tool, not a substitute for consulting a mental health professional.

Figure 7. Predict stress aplication

The detection page is the main feature that allows users to predict the classification of the level of stress in college students. This classification prediction process uses the Naïve Baiyes algorithm to analyze the data and provide prediction results. This system is expected to assist users in identifying and understanding their stress condition with the support of a more accurate real-time model, thus enabling rapid anticipation and action against indications of moderate or high stress so as not to disrupt the academic process of students. The chatbot will provide recommendations to users to consult with professionals or find references related to stress management. After the deployment process, the mobile application was tested to ensure the system functions correctly. The test results show that the application successfully accepts input, processes the data, and provides accurate classification results.

Model evaluation

Model evaluation is an important stage in assessing model performance after training. In this study, the Naïve Bayes model was evaluated using several metrics, such as accuracy, precision, recall, F1-Score, confusion matrix, and ROC curve with AUC. The evaluation results show that the Naïve Bayes model has excellent accuracy in predicting stress levels, with accuracy reaching 90%.

Table 3. Clasification report

Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
After SMOTE	90%	92%	90%	90%

The classification report results above show excellent performance in the data classification task. The precision and recall of the Naïve Bayes model show high values, although there is a slight decrease in identifying minority classes, such as high stress levels. The confusion matrix shows that the model has some errors in predicting the high stress category.

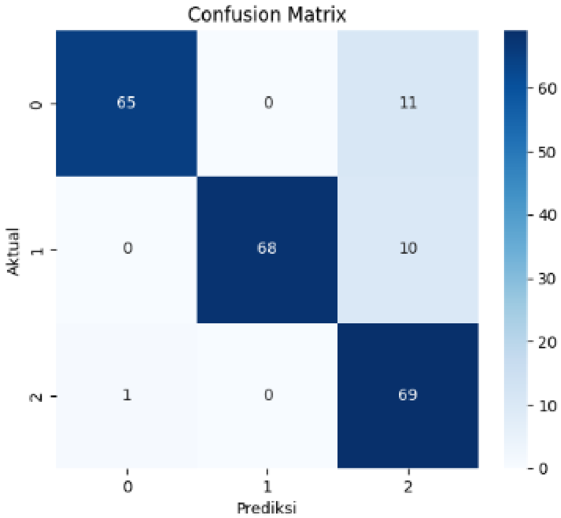

Figure 8. Confusion matrix

The confusion matrix shows that the model predicts with high accuracy for the three stress classes, with little prediction error between the normal stress class and the non-stress class. Furthermore, the ROC curve with AUC shows that the Naïve Bayes model can distinguish the classes well, although the best performance is achieved in the low stress category.

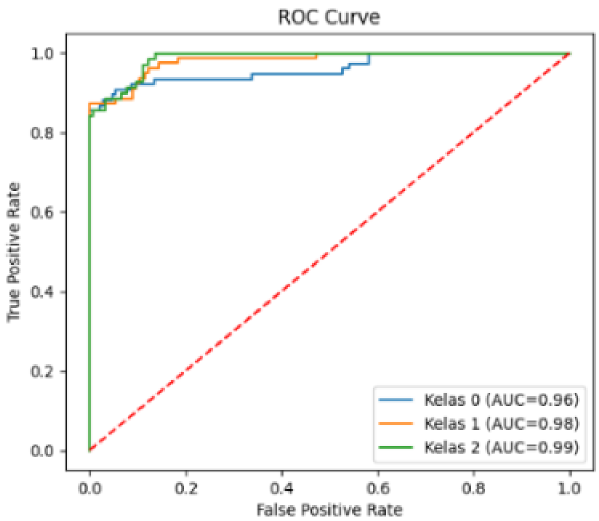

Figure 9. ROC AUC curve

The ROC Curve graph above shows that the model's performance in predicting the three classes, with high AUC for each class (0.96, 0.98, and 0.99), indicates that the model has excellent classification ability. With this good evaluation, it can be concluded that Naïve Bayes performs quite well in predicting stress levels in students.

Performance evaluation and results interpretation

Based on the assessment findings, the Naïve Bayes algorithm achieved an accuracy of 90%, precision of 92%, recall of 90%, and F1-score of 90%. In comparison, the Support Vector Machine (SVM) method obtained 89% accuracy, 90% precision, 89% recall, and 89% F1-score. These results indicate that Naïve Bayes slightly outperformed SVM across all evaluation metrics. The differences 1.18% in accuracy, 2% in precision, and 1% in recall suggest that while both models perform well in identifying students' stress levels, Naïve Bayes demonstrates slightly better overall classification performance.

Naïve Bayes model performs better than the SVM model in predicting student stress levels. In the meanwhile, SVM performs somewhat worse than Naive Bayes, despite having the benefit of using kernels to handle non-linear data. The sensitivity of SVM to data that is poorly distributed and the requirement for more intricate parameter adjustment to achieve the best results are probably the causes of this. Therefore, based on the information utilised in this study, Naive Bayes is better advised when predicting student stress levels.

By including pertinent characteristics, integrating with other algorithms like Random Forest or deep learning, and doing cross-university assessments to be more universal, the model may be enhanced for future growth. In summary, this study demonstrates that the Naive Bayes method may yield quite accurate results when used to forecast student stress. But with additional work, the model may become more precise and useful in assisting with early identification and better managing student stress.

CONCLUSION

In conclusion, the Naïve Bayes algorithm demonstrated superior performance in stress level classification compared to the Support Vector Machine, with slightly higher values across all evaluation metrics. These findings suggest that Naïve Bayes is a more suitable model for identifying student stress levels in this study.

The developed chatbot has also been integrated into a mobile application that uses Flutter and a Flask-based backend hosted with Ngrok to enable communication between the AI model and the user interface. This tool is expected to aid college students in assessing their own stress levels and provide first recommendations before seeking professional treatment. However, this research still has some limitations, such as the limited number of datasets and the need to improve the accuracy of the model with more complex machine learning methods. Therefore, further development can be done by increasing the amount of data, adopting deep learning techniques, and integrating psychology-based intervention features to provide a more comprehensive solution in student stress management.

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