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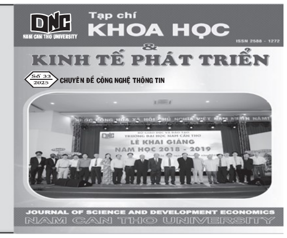

Predicting stress levels in the Stress-Lysis dataset using Sliding Window approach

Huynh Vo Huu Tri[2], Phan Thi Xuan Trang[2], Nguyen Anh Duy[1*], Ngo Ho Anh Khoi[2]

[1]*Adhightech Ltd., Vietnam*

[2]*Faculty of Information Technology, Nam Can Tho University, Vietnam*

[*]*Corresponding author: Nguyen Anh Duy (email: nguyenanhduy@adhigtechn.com)*

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ABSTRACT

The prevalence of depression, often exacerbated by heightened stress levels, is experiencing a significant surge, particularly among the youth, which correlates with an alarming rise in suicide rates within this demographic. This situation presents a compelling public health challenge that necessitates comprehensive investigation and intervention strategies. The present study aims to explore the utilization of a depression symptom database, employing classical machine learning techniques, with a focus on the Random Forest algorithm alongside other methodologies, to assess and diagnose stress levels. The objective is to facilitate timely interventions for individuals grappling with depressive symptoms. Accurate assessment of stress levels is essential for healthcare providers, as it enhances their ability to identify the mental health status of patients effectively and develop tailored treatment plans that may alleviate the severity of symptoms. This approach is particularly urgent in light of the concerning trends observed in mental health issues among younger populations.

TÓM TẮT

Tình trạng trầm cảm do căng thẳng quá mức đang gia tăng nhanh chóng, kéo theo sự gia tăng đáng lo ngại về số ca tự tử ở giới trẻ. Đây là một vấn đề cấp thiết đòi hỏi sự quan tâm và nghiên cứu chuyên sâu để tìm ra giải pháp can thiệp hiệu quả. Nghiên cứu này đề xuất sử dụng dữ liệu triệu chứng trầm cảm kết hợp với các thuật toán học máy cổ điển, trong đó có Random Forest, nhằm phân tích và đánh giá mức độ căng thẳng. Mục tiêu là phát hiện sớm các dấu hiệu bất ổn, từ đó hỗ trợ đưa ra các biện pháp điều trị phù hợp và kịp thời. Việc chẩn đoán chính xác mức độ căng thẳng không chỉ giúp đội ngũ y tế hiểu rõ tình trạng tâm lý của bệnh *nhân mà còn góp phần xây dựng phác đồ điều trị tối ưu, hạn chế sự trầm trọng của triệu chứng. Đặc biệt, trước thực trạng trầm cảm ngày càng phổ biến ở lứa tuổi trẻ, việc áp dụng phương pháp này trở nên quan trọng hơn bao giờ hết.*

1. INTRODUCTION

The issue of depression remains a pressing concern due to the indifference and lack of understanding about its severity. The causes of depression largely stem from excessive stress, leading to a significant decline in both mental and physical health, negatively affecting the daily lives and work of many who are suffering from it. Prolonged stress can lead to anxiety disorders, sleep disturbances, irritability or intense anger, difficulty concentrating, and, most dangerously, to the stage of depression, which is the cause of many suicides worldwide.

In some Asian countries like Vietnam, with the current societal and human development, the increasing workload and demands are inevitable, which in turn significantly increases the causes of stress, especially among young people. Prolonged stress, particularly among children who are preparing to go to school, is not just an issue in Vietnam but is a global concern. Numerous articles highlight the heavy pressure of exams and studies in neighboring countries like China. In the article "100,000 Chinese Students Commit Suicide Each Year Due to Academic Pressure", author Minh Thuy specifically mentions that the majority of student suicides in China are due to conflicts with teachers, academic pressure, grades, and criticism from parents. The author also cites statistics from The Economist, showing that the suicide rate among Chinese teenagers is the highest in the world, with the number reaching 100,000 annually. On average, every minute, 2 people commit suicide, and 8 others have similar intentions (Minh Thuy, 2020) [1]. Similarly, stars in the entertainment industry are also victims of numerous cases of suicide due to prolonged depression and stress. The article titled "The Young Deaths and Silent Killers of Korean Artists" provides many examples and cases where artists and celebrities have fallen victim to this issue. Specifically, the article mentions artists like Jonghyun, the lead singer of SHINee, who took his own life in 2017, and Sulli, known as Korea's "Snow Lily", who did the same in 2019, sparking a strong wave of shock in South Korea (Mi Van, 2022) [2].

Some provinces with strong academic performance, such as Da Nang city, have conducted studies on student stress, particularly within high school environments and among final-year students. Notably, there is a study titled "The Current State of Stress Levels in 12th Grade Students in Da Nang City" (Nguyen Thi Hang Phương & Dinh Xuan Lap, 2019) [3]. For data collection, the author surveyed 786 12th-grade students from various high schools in Da Nang, including Nguyen Thuong Hien, Phan Thanh Tai, Nguyen Trai, and Phan Chau Trinh. Of these students, 346 were male (44%) and 440 were female (56%).

In the study, published in the VJE Education Journal, the author presented specific statistics based on the survey, showing that 71.9% of students have experienced or are currently experiencing stress. Female students were found to be more stressed than their male counterparts, and students with average academic performance exhibited higher stress levels compared to those with good academic results. The author speculates that this is due to the fact that high school is a crucial period that significantly impacts each individual's future. At this age, students must meet many life demands, such as relationships with friends and teachers, as well as their own personal concerns, with academic results being their top priority, which influences other aspects of their lives.

The results of this study highlight the serious level of stress burdening students. Besides these issues, the severe and long-lasting impact of the COVID-19 pandemic has also led to numerous studies on its aftermath. One such study is titled "Academic Stress and Mental Well-Being in College Students: Correlations, Affected Groups, and COVID-19" (Barbayannis et al., 2022) [4]. The research team surveyed nearly 843 college students of various races, academic years, and genders, including male, female, and non-binary. They used two well-known survey methods: the SWEMWBS (Short Warwick-Edinburgh Mental Well-Being Scale), a shortened version of the WEMWBS mental health scale, and the PAS (Bedewy & Gabriel, 2015) [11].

The survey participants, aged 18 to 35, residing in the U.S., were surveyed online through the link (https://prolific.co). In October 2022, a total of 843 students participated in the survey using the mentioned methods and metrics. The study results showed that out of those surveyed, 678 students were affected by COVID-19, leading to increased stress levels. Among the participants, 80% were first-year students, who reported the lowest stress levels compared to other students. The researchers noted that the correlation between perceived academic stress and mental well-being among U.S. college students indicates that academic stressors, including academic expectations, workload, grades, and self-perception in learning, are just as important as current mental health. Additionally, the authors found that second-year students reported the highest levels of academic stress and the lowest levels of mental well-being compared to students in other academic years.

2. RESEARCH METHODS

Research on addressing the issue of stress remains challenging, as most diagnostic methods rely on manual techniques, such as posing questions and interpreting facial expressions, commonly referred to as observation-based methods. Despite the advancement of artificial intelligence algorithms, there is a notable lack of studies utilizing AI for stress diagnosis, which is a significant shortcoming. One of the few rare papers that apply machine learning to this issue is titled "Stress Detection via Keyboard Typing Behaviors by Using Smartphone Sensors and Machine Learning Techniques" (Sağbaş et al., 2020) [13]. This paper is particularly rare in its use of AI to address the problem of stress.

As mentioned in the title, the data for this study was collected using an application that operates on the Android operating system and involves four stages:

- Data collection for the calm state (CALM);
- Stress induction task;
- Data collection during the stress state (STRESS);
- Honest verbal survey.

The application was set up to collect 20 samples per second, and the data was stored on the phone's memory before being converted into a .csv file. The research team has made the dataset widely available to facilitate further research and provide it to those in need of the data, which can be downloaded at "https://tinyurl.com/2019-stress-detection-dataset".

With the collected dataset, the study utilized three algorithms such as kNN, Bayesian networks (BN), and Decision Tree for diagnostic research. The study also employed performance metrics such as Precision, Recall, Classification Accuracy (CA), Root Mean Square Error (RMSE), and F-Measure to compare the effectiveness of these methods. The final results showed that kNN achieved an impressive accuracy rate of 87.56%, followed by Decision Tree with 74.26%, and BN with 67.86%. After achieving these promising rates, another method, the Confusion Matrix, was applied to the algorithms. It was found that with the kNN algorithm, 13% of "calm" labels were misclassified as "stress". In the Decision Tree algorithm, 23% of "calm" labels were misclassified as "stress", and 29% of " stress" labels were mixed with "calm". Similarly, in the BN algorithm, these rates were 32.7% and 31%, respectively.

This study used a sensor and features that have not been utilized in previous literature and conducted two-class stress detection with a success rate of 87.56%. Since the sensor data was collected only during keyboard typing, no battery issues occurred. Additionally, it did not require a long time to make a decisive judgment for stress detection. Applying AI techniques solely for the purpose of solving problems related to data variation is a challenging obstacle. An example is the paper "Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT" (Rachakonda & Mohanty, 2019) [8]. In this paper, Laavanya and her research team used a Deep Neural Network (DNN) approach to address the "Stress-Lysis" dataset. The results were quite successful, with an accuracy rate exceeding 90%. However, this dataset is non-variant, and the DNN technique remains complex, requiring a high level of expertise and experience.

Currently, observation-based methods are still the preferred approach for studying stress, but these methods have many limitations and do not achieve as high accuracy as AI-based diagnostic methods. The use of machine learning for diagnosis, as demonstrated in the paper "Stress Detection via Keyboard Typing Behaviors by Using Smartphone Sensors and Machine Learning Techniques" is a rare breakthrough, achieving a relatively high accuracy rate of 87.56%. However, the drawback of this study is that it does not meet the current demand for continuously updated datasets.

In the experiment, we utilized various time series approaches, such as compares the balanced accuracy of four continuous learning machine learning algorithms, enhanced with EKI (Evolving with Klinkenberg's Idea) techniques: EKI-Adaboost, EKI-Decision Tree, and EKI-Random Forest across various models in terms of implementation and parameters. The goal is to compare, evaluate, and select the most suitable model for diagnosing stress levels. The project also aims to develop a test website where users can experience the process and access all necessary information about the content and operation of the stress level diagnostic method, contributing to building a society with strong mental health.

Currently, stress is still not fully recognized for the dangers it poses, with only a few countries truly prioritizing and researching stress to produce relevant datasets. During the search for data for this study, numerous datasets were found, but only a few had the most complete and usable parameters: “Human Stress Prediction” (Rajani, 2023) [15] published by Kreesh Rajani, “Stress Analysis in Social Media” (Bhatia, 2021) [5] published by Ruchi Bhatia, “Depression Anxiety Stress Scales Responses” (Greenwell, 2020) [6] published by Lucas Greenwell, and “2019_Stress_detection” (Sağbaş et al., 2019) [13] shared by Ensar Arif Sağbaş.

A brief description of the “Depression Anxiety Stress Scales Responses” dataset: This dataset consists of 39,775 data rows, making it a substantial dataset with 172 different labels, collected through a survey method available to anyone. It includes about 42 fields, each presented in a random order to each participant, along with a 4-point scale requiring users to indicate the frequency of their experiences. However, as these datasets may not be intended for diagnosis but for other purposes, and given that the data was collected in 2017, it is quite outdated for current use, making it unsuitable for experimental purposes.

The next dataset, “Stress Analysis in Social Media,” was published by Ruchi Bhatia on July 2, 2021. This dataset was developed from 190,000 posts across five social media platforms, with labels applied to 3,500 segments extracted from 3,000 posts. The aim was to perform psychological analysis to predict whether an individual is stressed. The dataset is divided into two separate files: dreaddit-test.csv with 716 samples and dreaddit-train.csv with 2,839 samples. It includes a large number of fields 116 in total representing stress-related parameters. However, many of these parameters have not been validated or clearly described, making this dataset too complex to be applied to research and development.

Similarly, the next dataset, “Human Stress Prediction”, was published by Kreesh Rajani, with the latest update on March 3, 2023. This dataset was built based on the “Stress Analysis in Social Media” dataset mentioned above, but has been refined and shortened by the author. It contains around 7 fields, including psychological state, post ID, post content, spacing between words, confidence level, timestamp, and finally, the dataset's label. This dataset is relatively simple, with only two labels indicating whether stress is present or not. However, despite being more concise than the previous dataset, it is still considered complex due to the abundance of characters and the presence of unclear data, which affects the accuracy of the study. Additionally, with only two labels (stressed or not stressed), it doesn't provide much practical value for research purposes. One dataset found in the paper titled “Stress Detection via Keyboard Typing Behaviors by Using Smartphone Sensors and Machine Learning Techniques” is the “2019_Stress_detection” dataset, which is labeled into two categories: “Stress” and “Calm”. This dataset comprises a total of 47 data fields and was constructed using data from 46 participants. It measures the impact of stress through accelerometer sensor data and gyroscope data based on typing behaviors on a smartphone's touchscreen. Due to its complexity, being divided into numerous CSV files to categorize participant

IDs, and its age, this dataset was not applied in this study.

Moving on to the “Stress-Lysis” dataset, this data was collected based on human physical activity, with stress levels being recorded and analyzed. The data was gathered using a smart device integrated with the Internet of Medical Things (IoMT), a specific application of IoT that includes devices and services primarily related to healthcare, such as body sensors and smart devices, all connected through IoT. The dataset includes 2001 samples and records data like human body humidity, body temperature, and the number of steps taken by the user. There are three labels for classifying stress levels: Low Stress, Medium Stress, and High Stress. Based on the datasets found, the dataset suitable for use in this study must meet several criteria: it must be numerical, have clearly defined classes, and be the most recently updated. Among the datasets reviewed, only the Stress-Lysis dataset (Senthil, 2023) [7] meets these requirements and is therefore the most appropriate choice for this study.

From a machine learning perspective, a significant challenge with current datasets is that centralized data often remains static over time, requiring a complete retraining when new data arrives. Classical algorithms necessitate a full retraining process with each new dataset addition, which is inefficient in dynamic real-world environments. For instance, in scenarios where real-world data has not yet arrived (but is expected to have similar characteristics to the current data), and the current data is sufficient to perform the task, waiting for complete real-world data may not be necessary. Instead, continuous learning algorithms can be employed to gradually improve the model in real-time as new data arrives.

Modern practice demands continuous real-time training to efficiently update predictive models, leading to numerous studies on continuous learning methods, also known as incremental learning or evolving learning. Continuous learning methods have been thoroughly studied and analyzed in (Khoi, 2015) [9]. One of the simplest methods is the sliding window technique, which has been applied to many classical algorithms to facilitate continuous learning (Bifet & Gavalda, 2007) [12]. This method continuously updates the model at each time point 't' by using the latest training data within a predefined window size 's'. The window size 's' can be based on time or the number of data points and typically overlaps with the previous window 'w'. A new model is trained at each iteration, reflecting an updated set of classes. The basic model of the sliding window technique is illustrated below:

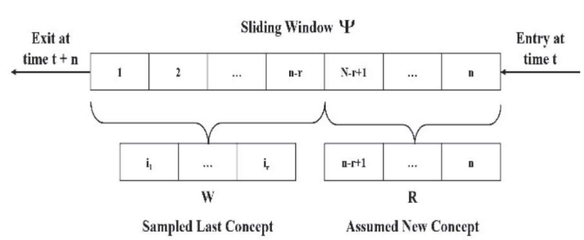

Figure 1. Operational model of the Sliding Window technique

Source: Raab Christoph, 2020 [10]

Given the reasons mentioned earlier, the "Stress-Lysis" dataset has been selected as the primary dataset for researching and solving the problem of diagnosing stress levels. The dataset includes features described as follows:

- Humidity: While humidity is typically known as the concentration of water vapor in the air, in this specific dataset, it refers to the moisture level of the human body, also known as sweat gland activity, measured by a smart sensor device. As the body's sweat increases, the current between two electrodes also increases, effectively turning the human body into a variable resistor. Sensors that detect humidity can be used to monitor sweat levels, which are controlled by the human central nervous system. Monitoring sweat production can help determine the stress and arousal levels of the monitored subject. Sweat gland activity is used as a variable in many physiological feedback applications, such as lie detection and emotion recognition. Normal sweating is referred to as diaphoresis, while excessive sweating disorders are known as hyperhidrosis, which is associated with emotional, occupational, and social stress. During the measurement process, the highest recorded value of humidity was 30 (unit: %) , and the lowest recorded value was 10 (unit: %).

- Temperature: The body temperature of a human, recorded as a percentage. Body temperature is a key symptom of any health issue. The temperature rate is the rate of change in body temperature over a certain period. By detecting patterns in temperature variations, a person's physical and mental state can be analyzed. The body temperature rate refers to the speed of temperature variation over a specific time period. Generally, temperature sensors can be classified into two types: contact temperature sensors, which measure temperature when placed on the body, and non-contact sensors, which measure infrared or optical radiation received from any part of the body. In this study, a contact temperature sensor is modeled to monitor the rate of change in body temperature. Throughout the measurement process, the maximum temperature recorded was 99 (unit: ◦F), while the minimum value observed was 79 (unit: ◦F).

- Step count: The number of steps taken is a significant factor, especially for subjects experiencing severe stress, where the step count tends to be higher. An accelerometer sensor measures the rate of velocity change of an object. These sensors usually include three separate accelerometers mounted orthogonally on a 3-axis physical system (x, y, and z). The forces causing acceleration can be static or dynamic. The sensed voltage is generated when tiny crystalline structures are affected by these forces. In this data collection, an accelerometer sensor is used to measure the step count of an individual. During the measurement process, the highest step count observed was 200 (unit: step), while the lowest value recorded was 0 (unit: step).

- Prediction label (Class): This is a crucial and decisive feature. The label can only take one of three values: “0”, “1”, or “2”. If the stress level is Level 1, the label will be 0; if it is Level 2, the label will be 1; and Level 3 will correspond to 2. There are a total of 2001 data points, with 501 labeled as Level 1, 790 as Level 2, and 710 as Level 3.

Currently, in Vietnam, there is no database on this issue, making it impossible to develop a predictive system immediately. Creating a dataset for this topic would be extremely costly in terms of effort, money, and time, potentially taking several years or even decades. This solution is nearly unfeasible at present. An alternative, less costly solution that has been used in similar cases is continuous learning.

The experiment uses an online learning model with a batch size of 1400, thus performing 1400 steps (Batch 1400). At each step, the system calculates the balanced accuracy metrics for the results. Traditional accuracy measures the proportion of correctly classified cases out of the total number, and it is generally reliable. However, this metric can be misleading in cases of severe class imbalance, such as a 90:10 ratio. For example, if 100 cases are tested with 99 cases being diseased and 1 case healthy, the balanced accuracy might appear high even if no meaningful model is present. Therefore, for imbalanced datasets, Balanced Accuracy (BA) is used. The choice of evaluation metrics depends on the problem's objectives and the composition of the dataset. In situations with significant class imbalance, where one class is underrepresented, traditional accuracy becomes unreliable. Therefore, metrics like the area under the ROC curve (AUC) and BA are preferred. Metrics such as balanced accuracy, sensitivity, and specificity are less effective for imbalanced data. For concordance detection, metrics based on the true positive rate/false positive rate, such as balanced accuracy, sensitivity, and F-Score, are appropriate. In contrast, for discordance detection, metrics based on the true negative rate/false negative rate, such as specificity, are suitable, although less common in practice. Sensitivity, balanced accuracy, and F-Score are criticized for ignoring the true negative cell of the confusion matrix and being prone to prediction bias (Powers, 2020) [14]. BA, which includes both the true positive rate and the true negative rate, provides a balanced evaluation, making it suitable for both concordance detection and imbalanced data situations (Khoi, 2015) [9]. BA is an important and simple metric for evaluating binary classifiers in the context of class imbalance, where one class is much more prevalent than the other. The formula for balanced accuracy (BA), which provides a practical and optimal evaluation, is:

Balanced Accuracy (BA) = ½ (Specificity + Sensitivity).

3. RESULTS AND DISCUSSION

By applying artificial intelligence methods, specifically algorithms such as EKI-Random Forest, EKI-Decision Tree, and EKI-Adaboost, combined with the Sliding Window method, this approach provides the most fairness in time series data accuracy when comparing the results from these algorithms. The average experimental results of the algorithms are illustrated using a chart (Figure 2):

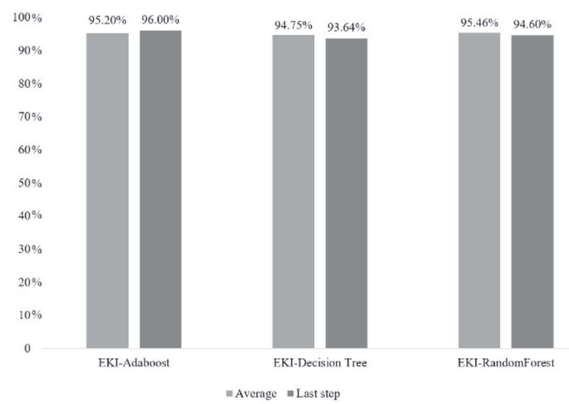

Figure 2. Average of BA and BA of the last batch of the four EKI algorithms

Looking at the chart, it is evident that most of the algorithms used in the experiment achieved a high average percentage. All three algorithms performed well (above 90%). Among them, Random Forest achieved the highest average percentage, with Decision Tree and Adaboost following closely, showing only a minor difference as Adaboost outperformed Decision Tree by just 0.25%. However, there is also a considerable gap between Random Forest and the other two algorithms, with a difference of 0.36% between Adaboost (the second-highest average) and Random Forest. Therefore, Random Forest proves to be the most suitable algorithm for this problem, showing the largest margin compared to the other two algorithms.

Table 1. Average of BA and BA of the last batch of the three EKI algorithms

EKI algorithms	**BA average** (%)	**The last step BA** (%)	**Standard deviation** (%)
EKI RandomForest	95.20	96.00	2.55
EKI DecisionTree	94.75	93.64	2.69
EKI AdaBoost	95.46	94.60	2.60

From a different perspective, when considering the final step's accuracy, Random Forest did not achieve a high percentage compared to Decision Tree, with a significant gap between the two. However, when compared to Adaboost, the final step percentages of both algorithms are relatively similar (both at 93%). Although Decision Tree achieved a high percentage at this final step, the difference is minimal, only 0.01%. Therefore, Random Forest remains a good choice for this problem instead of Decision Tree.

Aside from averaging the results of the algorithms, another approach is to compare the experimental model results based on 'n' to illustrate the improvement in balanced accuracy. This method provides a more comprehensive and detailed overview, allowing for a more accurate evaluation of the experimental model results. The improvement in balanced accuracy is illustrated in Figure 3:

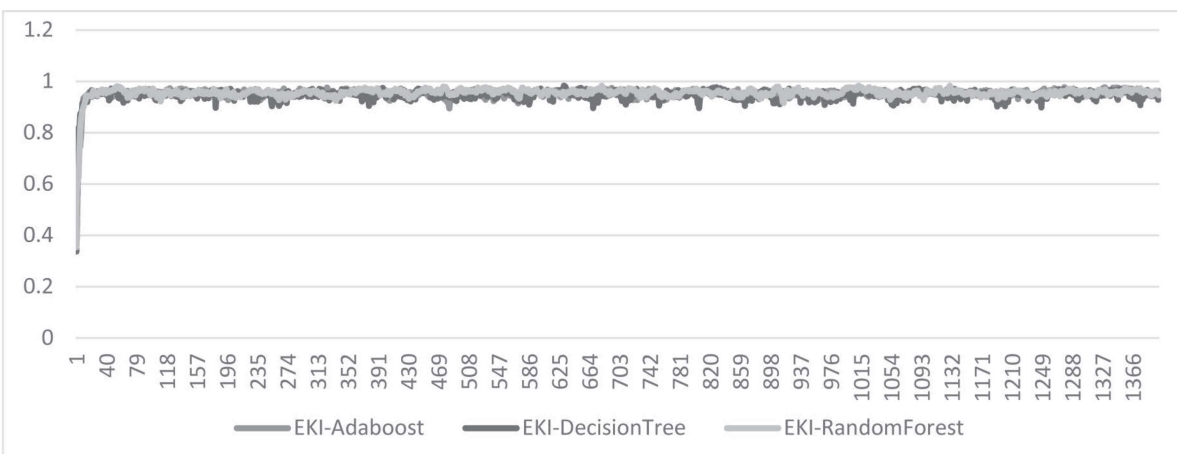

Figure 3. BA progression chart of the three EKI algorithms

Examining the chart of time series data above, we see that all three algorithms started at a relatively low point, with about 30%, and gradually increased over the first 10 to 30 steps before reaching stability. Although all methods show stability, the stability of Random Forest is significantly greater than that of the other two algorithms. Random Forest demonstrates its stability by consistently achieving a percentage above 90%.

From the perspective of real-world application, creating the necessary dataset for learning and prediction in the experimental environment in Vietnam is crucial. In Vietnam, due to the lack of related databases, immediately establishing a prediction system is not feasible. The initialization of a dataset for this topic, aimed at conducting learning processes and building a prediction system, requires substantial resources, which could take years or even decades. Currently, implementing this solution remains challenging. A more cost-effective approach, which has been applied in similar cases, is to use continuous learning models. Instead of waiting for a large amount of data to proceed with the learning process and build the prediction system, we can use a small amount of data to improve the model by continuously adjusting the basic concepts and gradually shifting the initial basic concept closer to a new basic concept (based on the Vietnamese dataset). This process is called "concept drift", and the model will be continuously improved by adding more accurate new data (data on Vietnam's land and crops). This method allows the prediction system to be used immediately and gradually improved through small errors in the model, rather than waiting a long time before the improved model can be utilized.

By combining the comparison of the final step and the average percentage of the four algorithms, we can conclude that EKI-Random Forest is the most worthy and suitable algorithm to apply for solving the stress level prediction problem. Based on the final results presented in the previous section, the Random Forest algorithm was selected to address the problem. The application will include features such as prediction functionality, running classical algorithms, a list of processed models, system configuration, and login. It will be installed on a web environment and will be divided into main functions: the algorithm installer (administrator or developer) and the diagnostician (user), described by the use case diagram below:

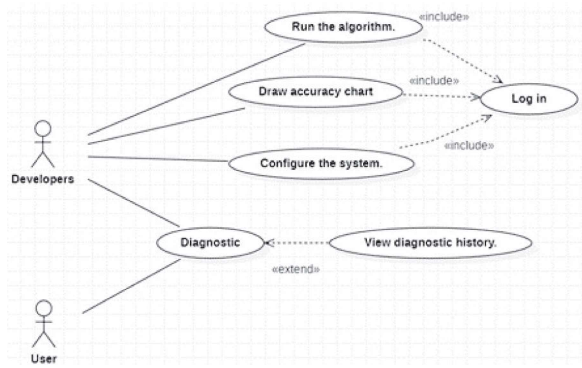

Figure 1. **Use case diagram**

Download the file "setup.zip", and after extracting it, you will find the following key files and folders: SETUP, DB, APP, INSTALL.bat, RunServer.bat, requirements.txt. Install the Python program by running the 'python-3.9.9-amd64.exe' file located in the SETUP folder. Install the necessary libraries to run the program by executing the CaiThuVien.bat file. Running the Remove.bat file will delete all program data. The database file is located in the 'DB' folder and is named Data.db, which can be opened using the 'DB Browser for SQLite.exe' tool located in 'DB\DB Browser for SQLite'. To change the administrator account, edit the file '\APP\static\dataUser.csv'.

To start the program, run the 'RunServer.bat' file or open the command line and run the command 'manage.py runserver'. The default server port is 8000, which can be changed by using the command 'manage.py runserver <port>'. When the command line displays 'Starting development server at http://127.0.0.1:8000/', you can access the main application page at 'http://127.0.0.1:8000/' (Figure 5).

Figure 2. **Website index**

4. CONCLUSION

This study focuses on comparing the Balanced Accuracy of three continuous learning algorithms improved with the EKI (Evolving with Klinkenberg's Idea) approach, including EKI-AdaBoost, EKI-Randomforest, and EKI-DecisionTree. The results indicate that the most optimal algorithm selected to address the problem is EKI-Randomforest. The project also aims to develop an experimental website where users can experience and check their mental health and then rely on the system's advice to create a plan to improve their well-being. With the introduction of this application, it will bring significant benefits, contributing greatly to the mental well-being of the Vietnamese people. The system will help promote social development, reduce some of the dangerous situations caused by stress, and assist doctors in diagnosing and providing timely treatment methods. Currently, the issue of depression stemming from increasing pressure and stress still lacks optimal treatment and solutions, leading to many tragic situations for those affected. This is especially true for young people attending school, as the issue of depression among younger populations is occurring more rapidly.

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