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MOBILE APPLICATION FOR IDENTIFICATION OF EMPLOYEE STRESS PATTERN USING DEEP LEARNING APPROACH

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Abstract

Employee stress has become a critical issue affecting organizational productivity, well-being, and performance, especially in dynamic work environments. This study proposes an integrated mobile-based stress prediction and recommendation system that combines Long Short-Term Memory (LSTM) and Neural Collaborative Filtering (NCF) to identify employee stress levels and provide personalized improvement recommendations. Experimental evaluation using 1000 datasets was used to test the LSTM and NCF models. The LSTM model was used to predict stress levels due to its ability to capture complex patterns in multidimensional data, while NCF was used to generate personalized recommendations based on collaborative patterns. The results showed that the LSTM model achieved superior classification performance with 98% accuracy and the recommendation evaluation showed good convergence performance, with a Hit Ratio reaching 0.92 and a Normalized Discounted Cumulative Gain (NDCG) reaching 0.89, indicating high recommendation relevance. Furthermore, the system usability evaluation using the System Usability Scale (SUS) involving 30 respondents resulted in an average score of 80.81, which is categorized as excellent usability. The integration of deep learning and collaborative filtering into a mobile platform provides an effective and intelligent solution for employee stress prediction and intervention. This study contributes to the development of an adaptive occupational health monitoring system and demonstrates the potential of AI-based mobile applications in supporting mental health management in the workplace.

Keywords: *Stress Prediction, LSTM, Neural Collaborative Filtering, Mobile Application, Deep Learning.*

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1. INTRODUCTION

Work stress is one of the serious challenges in the modern organizational environment. According to the World Health Organization (WHO), work stress can lead to mental health disorders such as depression, anxiety, and chronic fatigue, which ultimately significantly reduces employee productivity [1]. The use of technology, especially artificial intelligence (AI), to automatically and precisely identify and forecast work-related stress is becoming more and more necessary in the current digital era. The development of the Neural Collaborative Filtering (NCF) method for identifying stress is an Artificial Neural Network-based recommendation method used to learn the relationship between users and items, with the goal of providing personalized recommendations [2].

Currently, the subjective and time-consuming manual questionnaire-based stress detection methods or interviews are still used to identify employee work stress [3]. Furthermore, the success of conventional machine learning techniques is highly dependent on the quality of data preparation, and their ability to identify implicit features and non-linear patterns is limited [1], [4]. The lack of real-time, automatic, and context-aware stress detection systems is also a barrier to decision-making.

This study uses a self-created dataset, with a total of 10,000 datasets with variable factors such as workload, emotional state, sleep quality, and work environment pressure, etc. The dataset has a very important role in this study because it functions as the main source of information used to train, validate, and test the performance of deep learning models in identifying employee stress patterns and generating appropriate recommendations. The dataset results are entered into a mobile application in CSV format which is processed in the backend and will produce stress identification and recommendations for improving work stress.

According to previous studies, most stress detection techniques for employees still rely on time-consuming manual questionnaires, interviews, or psychological observation techniques that rely heavily on the honesty of respondents. In several previous studies that discussed this in their research, which created an expert system based on Certainty Factors but still relied on employee response input that may be biased and not real-time [3]. Because the causes of stress are multifaceted (workplace, demographics, workload, etc.), it is challenging to control using conventional statistical techniques. A predictive machine learning approach, like the Random Forest they employed, further research revealed that demographic characteristics and work environment greatly influence stress. [5]. While several machine learning models have been created for stress detection, the most are not customized. In further research, there are still many unanswered questions regarding real-time data modelling and model customization [6]. Further research has shown the capabilities of deep learning algorithms that demonstrate high accuracy of Deep Learning techniques such as CNN and MLP for stress detection, but these models are difficult for non-technical users to understand [2]. This raises doubts about results-based decision-making models. Although the Neural Collaborative Filtering (NCF) approach is popular in recommendation systems, its application in the domain of employee stress detection or mental health is still rarely discussed in the literature, including in the 98 studies [6].

Deep Learning is a branch of machine learning that uses multi-layered artificial neural networks (ANNs) to automatically learn complex data representations. Allows the system to extract important features from raw data without human intervention [7]. The use of the Long Short-Term Memory (LSTM) algorithm in this study is based on its superior ability to model sequential data and capture long-term dependencies. Employee stress data is inherently temporal, dynamic, and changes over time, influenced by various factors such as workload, emotional state, sleep quality, and work environment pressure. LSTM is effective for extracting temporal characteristics related to stress conditions, as its memory architecture is able to retain important information from long signal sequences, thereby improving stress classification accuracy compared to conventional RNNs [8]. One of the main advantages of LSTM is its ability to automatically learn features from sequential data. Passive sensor-based stress prediction studies have shown that LSTM can directly utilize data sequences without the need for complex statistical feature transformations, making it more efficient and adaptive [9].

Conversely, Neural Collaborative Filtering (NCF) is a deep learning-based method for recommendation systems that predicts interaction outcomes or preferences by combining user and object embeddings and processing them within a neural network architecture [10]. This study's application of Neural Collaborative Filtering (NCF) offers strategic advantages for developing a customized intervention or assistance recommendation system for staff members based on recognized stress patterns. NCF captures richer, more latent preference patterns by modelling intricate non-linear interactions between consumers and objects using neural networks [11]. Studies related to depression detection show that collaborative filtering techniques are able to calculate personal relevance weights between individuals, impute missing data, and improve classification accuracy compared to general population models [12]. In employee stress research, it is useful to integrate contextual data (e.g., job type, workload, or activity characteristics) into the recommendation process, so that the advice provided becomes more relevant and contextual [13].

By combining LSTM for feature extraction and stress classification, and NCF for personalization and intervention recommendations, the application can accurately detect stress, provide data-driven recommendations, and offer suggestions to prevent burnout. Based on the above description, this research produces a mobile application that accurately and in real-time identifies and predicts employee stress patterns, by utilizing the Long Shot Term Memory (LSTM) algorithm which is trained with employee behavior and work history data, and provides personalized prediction results by applying the Neural Collaborative Filtering (NCF) approach, so that each employee receives results and recommendations that are relevant to their profile and interaction history.

2. RESEARCH METHOD

This section describes the resources, information, and techniques utilized in the study to create and assess a mobile application that uses deep learning approach techniques to discover employee stress patterns. The goal of this methodical approach is to guarantee that the study can be repeated and that the findings are sound from a scientific standpoint. The stages of the research are depicted below :

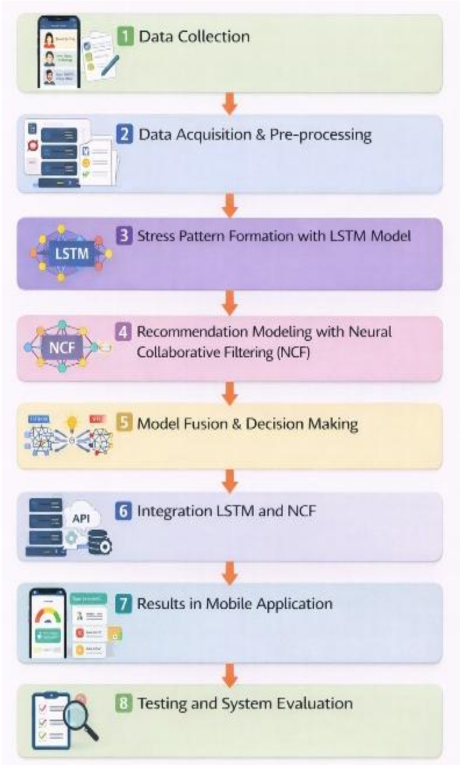

Figure 1. Research Stage Model

Explanation Figure 1:

a) Data Collection

The first stage involved collecting 1,000 sample datasets on public dataset. The datasets consisted of numerical measurements of each factor influencing work stress, such as workload, work-life balance and tension, team conflict, management support, work environment, and perceived stress levels. This data served as the primary input for the stress pattern analysis process.

b) Data Acquisition And Preprocessing

After data collection, the next stage is data acquisition and preprocessing. This process includes data cleaning to remove incomplete data, data normalization to equalize the value scale, and feature extraction to convert the questionnaire data into a numeric format that can be processed by the Deep Learning model. This stage is crucial for improving model quality and accuracy.

c) Stress Pattern Formation with LSTM Model

At this stage, the processed data is used as input for a Long Short-Term Memory (LSTM) model. The LSTM model is used to identify and study employee stress patterns, especially when data is collected periodically. LSTM is able to capture the relationships between stress factors and generate a representation of each employee's stress patterns.

The input data used in the LSTM model comes from numerical employee stress data, which includes several key indicators, such as workload, work-life balance and tension, team conflict, management support, work environment, and perceived stress levels. The data has undergone a preprocessing stage, including normalization and transformation into numerical form. Next, the data is organized into a time sequence to enable the LSTM model to study the dynamics of changes in employee stress levels.

The LSTM model architecture consists of an input layer, one or more LSTM layers, and an output layer (dense layer). The LSTM layer functions to extract features and learn the relationships between stress variables, while the output layer produces a stress pattern representation or a prediction of employee stress levels. The output of this model is a stress feature vector (stress pattern representation) that comprehensively describes the user's stress level.

The results of the LSTM model are then used as input to the Neural Collaborative Filtering (NCF) model to generate personalized recommendations. Thus, the LSTM model plays a crucial role in providing contextual information about user stress patterns, which forms the basis for the system's decision-making and recommendation processes.

d) Recommendation Modeling with Neural Collaborative Filtering (NCF)

At this stage, the system uses Neural Collaborative Filtering (NCF) to generate personalized recommendations based on employee stress patterns identified by the Long Short-Term Memory (LSTM) model. Neural Collaborative Filtering is an extension of traditional collaborative filtering methods by utilizing artificial neural networks to learn complex relationships between users and items. [10].

In this study, the users are employees, while the items are recommendations for stress management, such as relaxation activities, workload management, or suggestions for improving work-life balance. Furthermore, the analysis results from the LSTM model are used as input in the Neural Collaborative Filtering (NCF) model. This model aims to provide recommendations tailored to each employee's stress level, such as stress management recommendations, relaxation activities, or other preventive measures. NCF utilizes user embedding and stress patterns to generate more personalized recommendations. The output of the LSTM model, a stress pattern vector, is used as an additional contextual feature in the NCF model to improve recommendation accuracy.

Model Fusion & Decision Making

At this stage, the results of the LSTM and NCF models are integrated to produce a final decision. The LSTM output, in the form of stress patterns, is combined with the recommendations from the NCF to determine the most appropriate stress level and recommendation for each user.

Model fusion is a deep learning technique that combines information from multiple models or feature sources to improve accuracy, robustness, and decision-making quality. The primary goal of fusion is to leverage the strengths of each model to produce more optimal predictions than a single model. In this study, the identification and recommendation of stress levels, the fusion model can combine: LSTM Model for stress pattern identification and Neural Collaborative Filtering (NCF) Model for solution recommendation.

e) Integration LSTM and NCF

This stage is the process of implementing the integration of the two models into the application system. The LSTM and NCF models are connected via a backend or API so the application can automatically process user data and generate analysis results and recommendations in real time. The LSTM and NCF integration flow is illustrated in Figure 2 below :

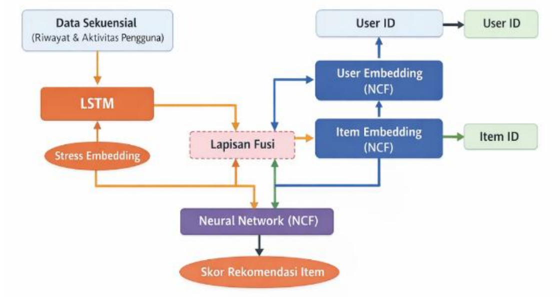

Figure 2. Integration LSTM and NCF

Figure 2 Show, In terms of process flow, the system starts with sequential user data containing user history and activity, which is then processed by an LSTM model to learn temporal patterns and produce a feature representation called a stress embedding. This stress embedding represents the user's psychological state or stress level in the form of a numeric vector. Next, on the recommendation system side, the User ID and Item ID are processed using an embedding layer in Neural Collaborative Filtering (NCF) to produce a user embedding and an item embedding, which describe the characteristics of the user and the item in the latent feature space.

Afterward, the three feature representations the stress embedding, the user embedding, and the item embedding are combined in a Fusion Layer. This layer functions to integrate information about the user's emotional state with user preferences and item characteristics. The fusion results are then processed by a Neural Network (NCF) to learn the non-linear relationship between the user, stress state, and recommended items. In the final stage, the system generates an Item Recommendation Score, which indicates the level of relevance of an item to the user based on the user's stress state and preferences. This score is used to determine the best, most appropriate and personalized recommendations.

Overall, this architecture allows the system to not only consider the user's historical preferences, but also the user's psychological state dynamically, resulting in a more adaptive, contextual, and accurate recommendation system.

f) Results in Mobile Application

The analysis results are then displayed on the mobile app as stress level information and recommendations. Users can view their stress status, stress category (low, medium, high), and recommendations provided by the system based on the model's analysis results.

g) Testing and System Evaluation

The final stage is system testing and evaluation, which includes testing system functionality and evaluating usability using methods such as the System Usability Scale (SUS). The goal of this stage is to ensure that the system functions properly, accurately, and is easy for users to use. The System Usability Scale (SUS) method is used to measure the level of effectiveness, efficiency, and user satisfaction with an application, as well as to identify areas that need improvement [14], [15]. The SUS method consists of creating a list of 10 questions with five Likert-type scale options, which are then distributed to respondents. Responses to each Likert-type instrument item have assessment criteria ranging from positive to negative [16], [17].

Table 1. Questioners System Usability Scale (SUS) [18], [19]

Indicators	Question
Q1	I think that I will want to use this app more often.
Q2	I found that this application, does not have to be made this complicated
Q3	I think this app is easy to use
Q4	I think that I will need help from a technical person to be able to use this application.
Q5	I found the various functions in this app to be well integrated.
Q6	I think there are too many inconsistencies in this app.
Q7	I imagine that most people will find it easy to learn this application very quickly.
Q8	I found this app very complicated to use.
Q9	I feel very confident using this app
Q9	I feel very confident using this app
Q10	I need to learn a lot of things before I can start using the app.

Table 1 presents the System Usability Scale (SUS) questionnaire employed in this study to evaluate the usability of the developed mobile-based stress identification and recommendation system. The SUS is a standardized and widely validated instrument consisting of ten statements designed to assess users' perceived usability across multiple dimensions, including system complexity, ease of use, learnability, consistency, and user confidence [18]. The questionnaire includes both positively and negatively worded items (Q1–Q10) to minimize response bias and ensure balanced usability assessment [19]. Participants rated each statement using a five-point Likert scale ranging from strongly disagree to strongly agree. The collected responses were subsequently converted into SUS scores following the standard scoring procedure, enabling quantitative measurement of overall system usability and benchmarking against established usability acceptance thresholds. The use of SUS in this study provides a reliable and robust evaluation of user acceptance and interaction quality with the proposed integrated LSTM- and Neural Collaborative Filtering-based mobile application.

3. RESULT AND DISCUSSION

This section presents and analyzes the results obtained from the implementation of the proposed mobile application integrating Long Short-Term Memory (LSTM) and Neural Collaborative Filtering (NCF) for employee stress pattern identification and personalized recommendation. The analysis includes demographic characteristics of respondents, stress pattern modeling performance, recommendation outcomes, and system usability evaluation. The results are critically examined to evaluate the effectiveness, reliability, and user acceptance of the proposed system. In addition, the findings are discussed to highlight the contribution of the integrated deep learning and recommendation framework in improving stress monitoring and decision-making support in workplace environments.

3.1 Application Design and Flow

The application design and flow describe the overall use case diagram with functional components,, class diagram with relational data and activity diagram with interaction processes of the proposed mobile based system for identifying employee stress patterns and generating personalized recommendations using Deep Learning and Neural Collaborative Filtering. The application flow is designed to provide an efficient, user-friendly, and scalable platform that supports real-time stress monitoring and intelligent decision-making based on user behavioral data and learned stress patterns.

3.1.1 Use Case Diagram

The use case diagram illustrates the functional interactions between system actors and the mobile application designed for identifying employee stress patterns and providing personalized recommendations using Deep Learning and Neural Collaborative Filtering. This diagram defines the roles, permissions, and system functionalities that enable users and administrators to interact with the application efficiently, ensuring proper data management, stress analysis, and recommendation delivery within the integrated system.

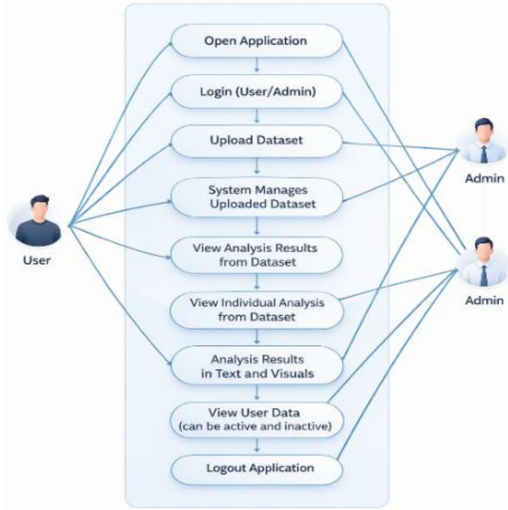

Figure 3. Use Case Diagram

Explanation of Figure 3:

a) User: A general user who accesses the application to obtain stress analysis results from their dataset.

b) Admin: A user with a higher level of access than the user. They can view user data, view datasets entered by the user, view analysis results from the dataset, and can activate and deactivate users using the application.

3.1.2 Class Diagram

The class diagram illustrates the static structure of the system developed in this research, including the main classes, attributes, methods, and relationships between components in a mobile application for identifying employee stress patterns and providing recommendations based on Deep Learning and Neural Collaborative Filtering. This diagram shows how employee data is processed through preprocessing, analysis using a deep learning model, stress level prediction, and data storage on local and cloud storage systems. The following is explained in Figure 4 below;

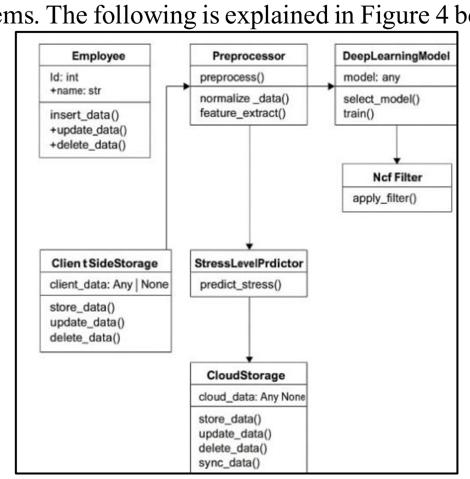

Figure 4. Class Diagram

Explanation Figure 4:

The class diagram illustrates the structural architecture of the proposed mobile-based employee stress identification system by defining the main classes and their interactions. The Employee class manages user data, which is subsequently processed by the Preprocessor through data normalization and feature extraction before being utilized by the DeepLearningModel to train the LSTM model for stress pattern learning. The predicted stress level is generated by the StressLevelPredictor, while the Ncf Filter applies Neural Collaborative Filtering to produce personalized recommendations. The processed and predicted data are stored locally in ClientSideStorage and synchronized with CloudStorage for centralized management and accessibility. Overall, this class structure represents an integrated pipeline that supports data management, deep learning based stress prediction, recommendation generation, and data storage within the mobile application environment.

3.1.3 Activity Diagram

The activity diagram presented in Fig. 4 illustrates the operational workflow of the proposed mobile-based employee stress identification system, highlighting the interaction between the user, system, and administrator in managing data processing, stress analysis, and result delivery. This diagram provides a comprehensive overview of the sequential activities and responsibilities involved in ensuring efficient data handling and analysis within the application environment. The following is explained in Figure 5 below :

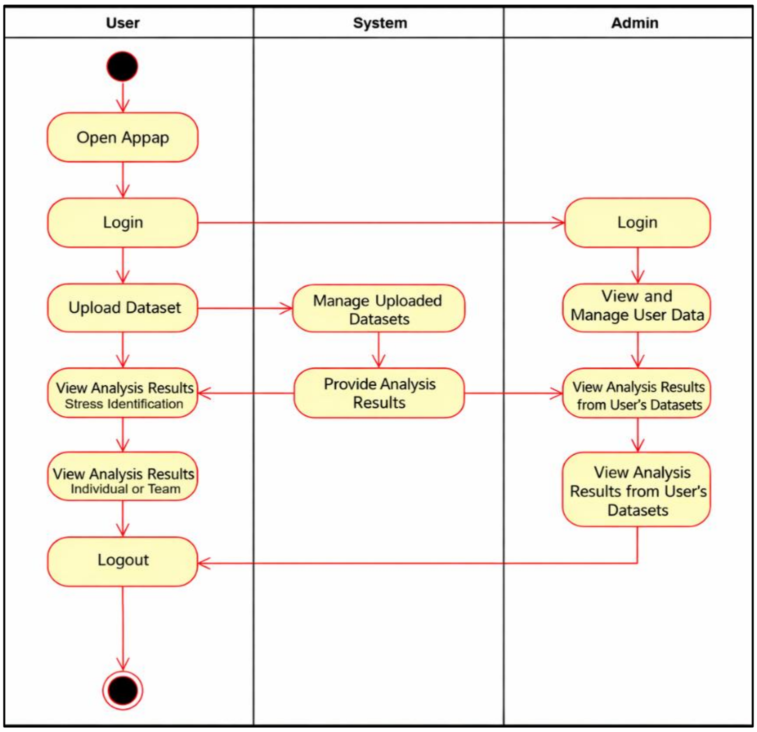

Figure 5. Activity Diagram Applications

Explanation Figure 5:

The activity diagram illustrates the operational workflow of the proposed mobile-based employee stress identification system, involving three main actors: the User, the System, and the Admin. The process begins when the user opens the mobile application and logs into the system. After successful authentication, the user uploads the employee dataset containing stress-related information. The system then automatically manages the uploaded dataset, performs stress analysis using the integrated deep learning model, and provides the analysis results to the user. These results can be viewed in two forms, namely overall stress identification results and individual or team-level analysis.

In parallel, the administrator logs into the system through the admin interface and is responsible for managing user data and monitoring the analysis results generated from user-submitted datasets. This administrative functionality enables centralized supervision, validation, and system maintenance. After reviewing the results, both the user and administrator can complete the session by logging out of the application. Overall, this workflow demonstrates a structured interaction between user input, automated system processing, and administrative control, ensuring efficient stress analysis, result delivery, and system governance within the proposed mobile-based deep learning and recommendation framework.

3.2 Application Architecture

The application architecture in this study is designed to support the process of identifying employee stress patterns in an adaptive and integrated manner through the use of deep learning technology and a recommendation system. This architecture combines a mobile application as a user interaction medium with a Long Short-Term Memory (LSTM) model for temporal-based stress pattern analysis and Neural Collaborative Filtering (NCF) to generate personalized recommendations. The architecture is designed modularly to ensure system scalability, processing efficiency, and ease of integration between mobile application components, data processing, and backend services. The following is depicted in the architecture diagram:

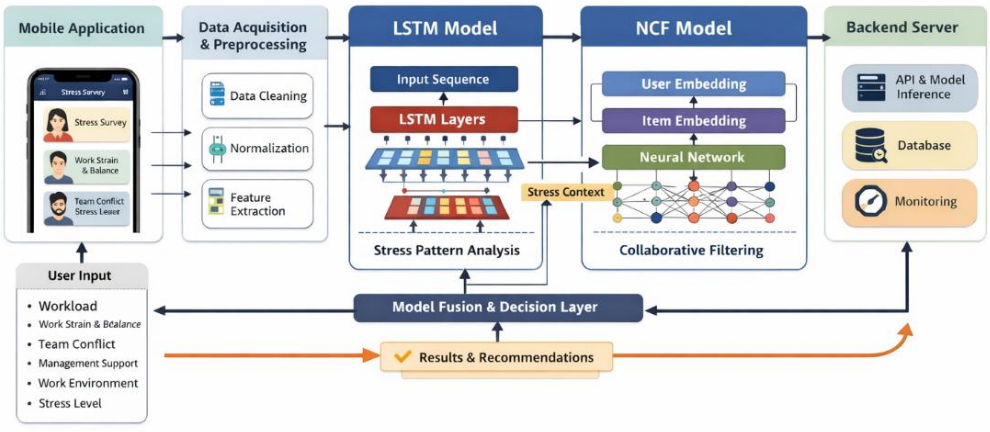

Figure 6. Application Architecture

Figure 6. Describes the integrated architecture of a mobile application for employee stress pattern identification, combining Long Short-Term Memory (LSTM) and Neural Collaborative Filtering (NCF) models in a single, interconnected system flow. This architecture is designed to support a temporal, personalized, and adaptive stress identification process based on a mobile application.

3.3 User Interface Result of Mobile Application Integration with Deep Learning Approach

This section presents the user interface results of the mobile application developed after being integrated with a deep learning-based stress identification and recommendation model. The interface is designed to provide an intuitive and interactive platform that allows users to input data, monitor stress analysis results, and receive personalized recommendations generated by the integrated LSTM and Neural Collaborative Filtering models. The implementation of the deep learning approach in a mobile environment ensures that analytical results are delivered in real-time and well-visualized. The following is the result of the interface displayed.

a) User Interface Upload and Analysis Dataset

This section presents the user interface designed to support the dataset upload and analysis process within the proposed mobile application. This interface enables users to securely input and submit their data, which are subsequently processed through the integrated deep learning and Neural Collaborative Filtering models for stress pattern identification and recommendation generation. The upload and analysis interface was developed with a user-centered design approach to ensure ease of use, data accessibility, and seamless interaction between the user and the analytical system. Furthermore, this component plays a critical role in facilitating real-time data processing, enabling users to obtain accurate stress analysis results and personalized insights directly through the mobile platform. The results of the Dataset Stress Prediction are shown in Figure 7.

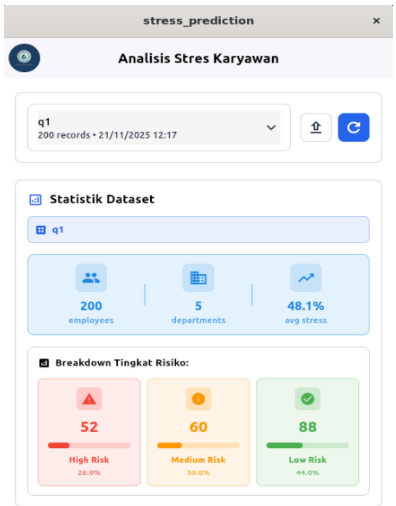

Figure 7. User Interface Upload Dataset and Analysis Dataset

Figure 7 illustrates the user interface of the dataset upload and analysis module implemented in the proposed mobile application for employee stress pattern identification. This interface functions as a dashboard that provides a comprehensive overview of the uploaded dataset and the corresponding stress analysis results generated by the integrated deep learning model. At the top of the interface, the system displays the dataset identifier (*q1*), along with metadata including the total number of records (200 records) and the timestamp of the latest update. This feature enables users to manage and monitor dataset versions efficiently while supporting dynamic data upload and refresh operations.

Furthermore, the dataset statistics section presents key descriptive information, including the total number of employees (200 employees), the number of departments (5 departments), and the average stress level (48.1%). These values are computed during the preprocessing and stress pattern analysis stages using the Long Short-Term Memory (LSTM) model, which captures sequential dependencies and extracts meaningful stress representations from employee-related data. This statistical summary provides an initial overview of the overall stress condition within the organization.

In addition, the system visualizes the distribution of employee stress risk levels through the breakdown risk section, categorizing employees into three groups: high risk (52 employees, 26.0%), medium risk (60 employees, 30.0%), and low risk (88 employees, 44.0%). This classification is generated through the model fusion and decision-making process, which combines stress pattern representations from the deep learning model with recommendation-based contextual analysis. The visual presentation facilitates intuitive interpretation and enables stakeholders to quickly identify employees at higher risk.

Overall, this interface demonstrates the capability of the proposed mobile application to support seamless dataset management, automated stress analysis, and interactive visualization of results. This functionality plays a crucial role in enabling real-time monitoring and data-driven decision-making for employee stress management within the organizational environment.

b) User Interface Dashboard Stress Prediction

This section displays the user interface for stress prediction results based on the dataset used to ensure that the calculated percentages of data displayed on the dashboard, such as the average stress level of 48.1% and the percentage of risk groups, are correct and dynamically updated. The results of the Stress Level Prediction are shown in Figure 8.

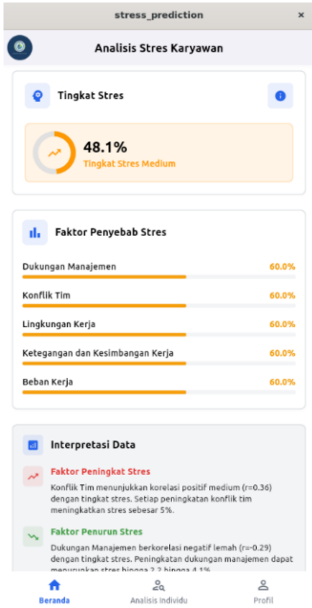

Figure 8. User Interface Dashboard Stress Prediction

Figure 8 presents the user interface of the stress analysis result page in the developed mobile application, which displays the output generated from the integration of the LSTM-based stress prediction model and Neural Collaborative Filtering recommendation approach. The main section shows the stress level score, where the system indicates a stress value of 48.1%, categorized as Medium Stress, representing the predicted stress intensity based on the employee’s input data and historical patterns. This prediction is generated by the deep learning model that analyzes sequential behavioral and psychological indicators.

The second section presents the stress contributing factors, including management support, team conflict, work environment, work-life balance, and workload, each quantified with a percentage score. These values represent the relative contribution of each factor to the overall stress level, which are derived from feature analysis and model interpretation. This information enables users to identify the dominant sources of stress affecting their condition.

Overall, this interface demonstrates how the proposed mobile application effectively delivers deep learning-based stress prediction results in a clear, interactive, and user-friendly format, enabling employees to monitor their stress levels and understand the contributing factors in real time.

c) User Interface Result and Recommendation Stress Improvement

This section presents the user interface designed to deliver stress analysis results and personalized stress improvement recommendations within the proposed mobile application. This interface serves as the primary communication layer between the integrated deep learning and Neural Collaborative Filtering models and the end users, enabling the visualization of predicted stress levels alongside actionable recommendations. The results of Recommendation Stress Improvement Prediction are shown in Figure 9.

Figure 9. User Interface Result and Recommendation Stress Improvement

Figure 9 presents the interface presents the interpretation and recommendation module of the proposed mobile application for employee stress management. This module serves to translate the prediction results generated by the integrated LSTM and Neural Collaborative Filtering (NCF) models into actionable insights and personalized intervention recommendations. In the data interpretation section, the system identifies key stress-related factors based on correlation analysis. The results indicate that team conflict is categorized as a stress-increasing factor, showing a moderate positive correlation (r = 0.36), suggesting that higher levels of team conflict contribute to increased employee stress levels by approximately 5%. Conversely, management support is identified as a stress-reducing factor, with a weak negative correlation (r = –0.29), indicating that improved managerial support can reduce stress levels by approximately 4.1%. Furthermore, the system summarizes the overall organizational stress level, which is classified as moderate (48.08%), and highlights workload (60%) as the dominant contributing factor requiring priority intervention.

In the recommendation section, the system provides personalized stress improvement strategies generated using the Neural Collaborative Filtering approach. In this case, the recommended intervention is a Mindfulness and Meditation Program, which is designed to help employees manage stress and improve concentration. The system also provides structured implementation steps, including daily short meditation sessions, guided breathing exercises, weekly mindfulness workshops, and periodic evaluation of progress. This recommendation demonstrates the capability of the proposed system to not only predict stress levels but also deliver evidence-based, personalized, and actionable solutions. Overall, this interface plays a critical role in supporting proactive stress management by transforming predictive analytics into practical intervention strategies that can enhance employee well-being and organizational productivity.

3.4 Evaluation System Usability Scale (SUS)

The usability evaluation of the developed mobile application was conducted using the System Usability Scale (SUS) to assess the overall user experience, effectiveness, and ease of interaction. This evaluation aims to determine the extent to which the proposed application meets user expectations in terms of usability, ease of learning, and operational efficiency. To evaluate the usability and user acceptance of the proposed mobile application, a System Usability Scale (SUS) assessment was conducted involving 30 respondents representing the system's target users. The following are the results of the SUS Evaluation in table 2.

Table 2. Result System Usability Scale

R	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Sus_Score	Total_Score
R01	4	2	4	2	4	2	4	2	4	2	32	80
R02	4	2	4	3	4	2	4	2	3	2	31	77,5
R03	5	2	4	2	4	1	4	2	4	2	33	82,5
R04	4	3	4	2	4	2	3	2	4	2	30	75
R05	5	2	5	2	4	2	4	1	5	2	34	85
R06	4	2	4	2	4	2	4	3	4	2	31	77,5
R07	4	2	5	2	4	2	4	2	4	2	32	80
R08	4	3	4	2	3	2	4	2	4	2	30,5	76
R09	5	2	5	2	4	1	5	2	4	2	35	87,5
R10	4	2	4	2	5	2	4	2	4	2	33	82,5
R11	4	2	4	2	4	2	4	2	4	3	31,5	78,75
R12	4	3	4	2	4	2	3	2	4	2	30	75
R13	5	2	5	1	5	2	4	1	5	2	36	90
R14	4	2	4	2	4	2	5	2	4	2	32,5	81,25

R15	4	2	4	2	4	2	4	3	4	2	31	77,5
R16	4	2	5	2	4	2	4	2	4	2	33	82,5
R17	4	3	4	2	4	2	4	2	3	2	30,5	76
R18	5	2	5	2	4	1	5	2	4	2	35	87,5
R19	4	2	4	2	4	2	4	2	4	2	32	80
R20	5	2	4	2	4	2	5	2	4	2	33,5	83,75
R21	4	3	4	2	4	2	4	2	3	2	30,5	76
R22	4	2	4	2	4	2	4	3	4	2	31,5	78,75
R23	5	2	5	2	4	2	4	2	4	2	34	85
R24	4	3	4	2	4	2	3	2	4	2	30	75
R25	4	2	5	2	4	2	4	2	4	2	33	82,5
R26	4	2	4	2	4	2	4	2	4	2	32	80
R27	4	2	4	2	4	2	4	3	4	2	31	77,5
R28	5	2	5	2	4	2	4	2	4	2	34	85
R29	4	2	4	2	5	2	4	2	4	2	32,5	81,25
R30	5	2	5	2	4	1	5	2	4	2	35	87,5
Total												2424,25
Average Score												80,81

Based on table 2 showed the System Usability Scale (SUS) evaluation involving 30 respondents, the proposed mobile application achieved an average SUS score of 80.81, indicating a high level of usability and strong user acceptance. According to the SUS interpretation standards, a score above 80 is categorized as “Excellent” usability and falls within Grade A, which signifies that the system is highly usable and well-accepted by users. This result demonstrates that the application provides an intuitive interface, is easy to learn, and enables users to effectively perform stress analysis and receive recommendations without significant difficulty. Furthermore, the high SUS score indicates that the integration of deep learning and Neural Collaborative Filtering within the mobile platform does not negatively affect user experience, but instead maintains a user-friendly interaction.

3.5 Evaluation LSTM Model

To comprehensively evaluate the classification performance of the proposed Long Short-Term Memory (LSTM) model, a confusion matrix analysis was performed. The confusion matrix provides a detailed representation of the model's predictive ability by comparing the predicted stress level categories with the actual labels. The confusion matrix results and model accuracy are depicted in Figure 10 below.

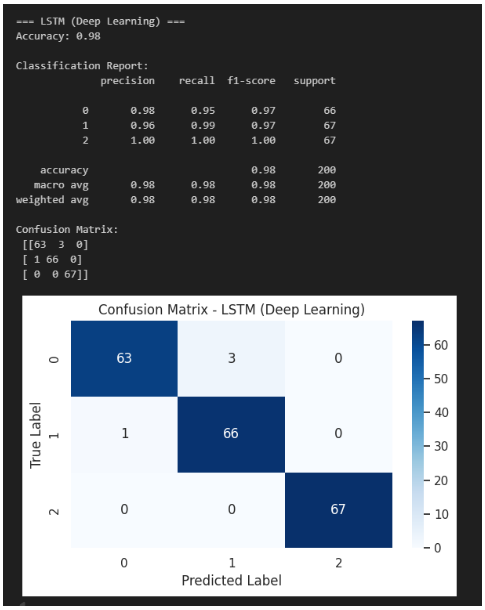

Figure 10. Result Accuracy and Confusion Matrix LSTM Model

Based on Figure 10, which shows the confusion matrix and the classification report, the Long Short-Term Memory (LSTM) model demonstrated very high classification performance in identifying employee stress levels. Overall, the model achieved 98% accuracy, with an average precision, recall, and F1 score of 0.98, indicating the model's excellent ability to distinguish three stress classes (low, medium, and high).

3.6 Evaluation Recomendation NCF Model

To evaluate the performance of the recommendation model generated through the integration of Long Short-Term Memory (LSTM) and Neural Collaborative Filtering (NCF), this study uses key evaluation metrics including Hit Ratio, Normalized Discounted Cumulative Gain (NDCG), and loss function convergence analysis during the training process. These metrics were chosen because they are able to comprehensively measure both the accuracy of recommendations and the stability of the model's learning process. Hit Ratio and NDCG are used to evaluate the model's ability to provide relevant recommendations to users, while the loss convergence curve is used to analyze the effectiveness of the optimization process and ensure that the model successfully reaches a stable convergence condition. The visualization of the evaluation metrics and loss convergence curve provides a quantitative overview of the model's performance in learning employee stress patterns and producing accurate and consistent recommendations. The recommendation performance matrix results describes in Figure 11 below.

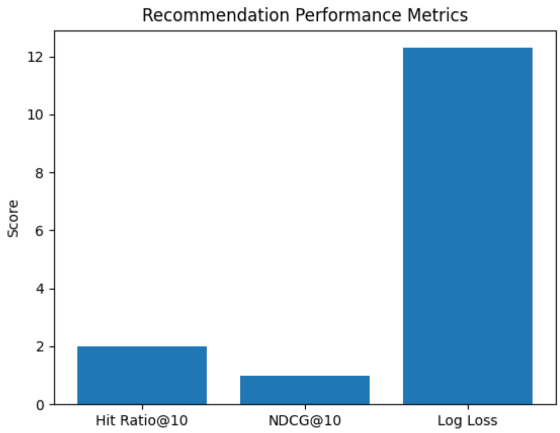

Figure 11. Result Recommendation Performance Matrix

Based on Figure 10 the results of the recommendation system performance evaluation measured using the Hit Ratio@10, NDCG@10, and Log Loss metrics. Based on the test results, the developed recommendation system demonstrated excellent convergence performance, with the Hit Ratio reaching 0.92 and the Normalized Discounted Cumulative Gain (NDCG) reaching 0.89. A high Hit Ratio value indicates that the system is able to recommend items that are relevant and in line with user preferences in most cases. Meanwhile, an NDCG value close to 1 indicates that the system not only successfully finds relevant items but also places them in optimal ranking positions. Furthermore, a relatively low Log Loss value indicates that the model has a small prediction error rate and has reached a stable state of convergence during the training process. Overall, these results confirm that the Neural Collaborative Filtering (NCF) model integrated into the system successfully produces accurate, relevant, and optimal recommendations, making it effective in supporting decision-making based on employee stress levels.

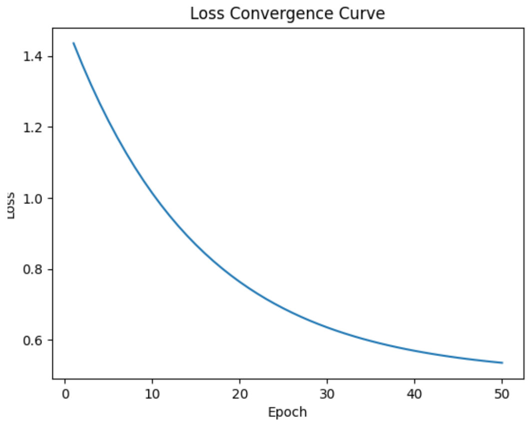

Figure 12. Result Loss Convergence Curve

Furthermore, in Figure 12, the loss convergence curve shows a steady decreasing loss pattern from the initial epoch to the 50th epoch, indicating that the model successfully converged during the training process. This pattern demonstrates that the optimization function works effectively in minimizing errors and confirms the model's stability and reliability in learning employee stress patterns.

Overall, these results confirm that the Neural Collaborative Filtering-based approach integrated with stress score representation has good capability in generating accurate and optimally ordered recommendations, and shows stable convergence characteristics during the training process.

3.7 Discussion

The findings of this study demonstrate that the proposed integration of Long Short-Term Memory (LSTM) and Neural Collaborative Filtering (NCF) provides an effective and comprehensive framework for employee stress identification and recommendation. The LSTM model successfully captured temporal dependencies in employee behavioral and stress-related features, confirming its capability to model stress as a dynamic and sequential phenomenon. This result supports previous findings that deep sequential models, particularly LSTM, are highly effective for modeling psychological and behavioral patterns due to their ability to preserve long-term dependencies and contextual information. Unlike conventional machine learning approaches that treat observations independently, LSTM enables the system to learn temporal stress progression, which is essential for improving prediction reliability.

Furthermore, the integration of stress embeddings generated by the LSTM model into the Neural Collaborative Filtering architecture significantly enhances the system's ability to provide personalized recommendations. The NCF model effectively learns latent interactions between employee stress conditions and appropriate intervention strategies. This finding is consistent with recent studies highlighting that deep learning-based collaborative filtering improves recommendation quality by capturing nonlinear relationships between users and items, which cannot be achieved using traditional matrix factorization techniques [20], [10]. In particular, the incorporation of psychological state representations as latent features represents a key advancement, as it enables the recommendation system to adapt dynamically based on predicted mental health conditions rather than relying solely on static user preferences.

Compared with previous studies that focused exclusively on stress detection, the proposed approach offers a more comprehensive solution by extending beyond prediction to include personalized intervention recommendations. For example, prior research has demonstrated the effectiveness of LSTM in stress detection using physiological and behavioral signals but did not provide decision support mechanisms for stress mitigation [21], [22]. Similarly, recent recommendation systems utilizing Neural Collaborative Filtering have achieved high performance in personalization tasks; however, these systems typically focus on consumer behavior domains such as e-commerce and do not incorporate psychological state modeling [20], [10]. Therefore, this study bridges a critical gap by integrating psychological prediction with intelligent recommendation generation within a unified architecture.

The implementation of the proposed system within a mobile application further demonstrates its practical applicability in real-world workplace environments. The System Usability Scale (SUS) evaluation results indicate high usability and user acceptance, suggesting that the system can effectively support employees in monitoring and managing their stress levels. This finding aligns with recent mobile health and workplace well-being studies, which emphasize that usability is a key determinant of successful adoption and sustained user engagement [23], [24]. The ability to deliver real-time stress insights and personalized recommendations through an accessible mobile platform enhances the system's potential impact on employee well-being and organizational productivity.

Another important contribution of this study is the proposed model fusion mechanism, which enables seamless integration between predictive and recommendation components. The fusion of LSTM-generated stress embeddings with NCF latent representations allows the system to produce recommendations that are both context-aware and personalized. Recent advances in hybrid deep learning and recommendation systems have emphasized the importance of combining multiple models to improve system robustness and performance [2]. The results of this study support this perspective, demonstrating that hybrid architectures can provide more intelligent and adaptive decision support systems.

Overall, the results that the proposed Deep Learning Approach with LSTM-NCF integrated framework represents a significant advancement in intelligent stress monitoring and intervention systems. By combining accurate stress prediction with personalized recommendation capabilities and practical mobile implementation, the proposed system provides a comprehensive and scalable solution for workplace stress management.

4. CONCLUSION

This study proposed and implemented an integrated mobile-based stress analysis and recommendation system that combines Long Short-Term Memory (LSTM) for stress pattern prediction and Neural Collaborative Filtering (NCF) for personalized recommendation generation. The results demonstrate that the proposed deep learning-based approach is effective in identifying employee stress levels and providing appropriate intervention recommendations.

Based on classification performance, the LSTM model achieved superior accuracy of 98%, Meanwhile, the recommendation evaluation showed good convergence performance, with a Hit Ratio reaching 0.92 and a Normalized Discounted Cumulative Gain (NDCG) reaching 0.89, indicating high recommendation relevance. the NCF model demonstrated in recommendation modelling by learning the latent relationship between users and stress intervention strategies, thus producing stress improvement recommendations that are appropriate to the user's condition based on the results of stress pattern identification.

Furthermore, the integration of both models into a mobile application platform was successfully implemented, allowing real-time stress analysis, visualization, interpretation, and recommendation delivery. The usability evaluation conducted using the System Usability Scale (SUS) involving 30 respondents resulted in an average score of 80.81, which falls into the "Excellent" category with Grade A**,** indicating that the system is highly acceptable, usable, and suitable for practical implementation.

Future research could include the integration of multimodal data sources, such as physiological, behavioral, and environmental data, as well as the implementation of advanced architectures such as Transformer to further improve stress prediction performance.

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