Mobile App for Detecting Work-Related Stress Using Acoustic Biomarkers and Machine Learning

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Abstract. The rising prevalence of work-related stress, particularly in remote settings, requires innovative and accessible monitoring solutions. In response, this paper details the development and validation of a mobile application that uses machine learning to detect work-related stress through acoustic biomarkers from the user's voice. The system relies on a Decision Tree model to analyze key vocal features, including Mel-Frequency Cepstral Coefficients (MFCCs), pitch, and Root Mean Square (RMS) energy, for stress classification. Model robustness and generalizability were rigorously assessed using Leave-One-Out cross-validation. The final model achieved a 75% in accuracy, precision, and recall. These findings validate the efficacy of using acoustic biomarkers as non-invasive indicators of stress. This research contributes to a functional prototype, offering a significant step toward practical, low-cost tools for periodic mental health monitoring scheduled by leaders in the context of modern work environments.

Keywords: work stress, machine learning, employees, acoustic biomarkers.

1 Introduction

Work-related stress has become an increasing concern due to the shift to remote work, especially after the pandemic. While this work model offers flexibility and autonomy, it has also brought risk factors like social isolation, work overload, and difficulty separating personal and professional life. Several studies have pointed out that remote work can increase the overall workload, exposing employees to job insecurity and, as a result, negatively impacting their engagement and emotional well-being [1]. At the same time, a specific type of stress, known as hindrance stress, has emerged. It not only affects individual performance but also family well-being, as workers find it hard to set boundaries between their work and personal lives [2]. The impact of telework has also been studied from an occupational health perspective. A study conducted in India found that work-related stress significantly affects motivation, job satisfaction, and performance, mainly due to the lack of co-worker interaction and prolonged isolation [3]. On top of that, the search for meaning at work can lead to emotional overload and burnout [4].

Even with the growing body of literature on remote work, there is still a gap when it comes to early detection of stress indicators in remote workers. In this context, using machine learning and acoustic biomarkers is emerging as an innovative way to identify stress patterns in human speech. This could allow for timely intervention before stress negatively affects employee performance or health [3][5]. Recent studies have already shown the potential of wearable devices to monitor stress in real time. For example, [6] developed a stress recognition system based on heart sounds captured through in-ear devices, achieving results similar to traditional ECG recordings [6]. Similarly, in [7] the authors created a smartwatch equipped with Heart Rate Variability (HRV) sensors and sweat cortisol detection to track stress continuously and non-invasively. Another interesting approach comes from [8], where the authors combined vocal biomarkers with deep learning models to detect stress levels in employees. Along the same lines, authors in [9] and [10] used LSTM neural networks to identify psychological disorders from voice signals, achieving a 98% accuracy rate in classifying stress. The integration of these technological advances with personalized mobile solutions opens the door to more accessible, continuous, and objective telemedicine tools.

In this context, this paper introduces a mobile application for the early detection and monitoring of work-related stress through voice analysis and machine learning. Unlike continuous monitoring systems, the app allows leaders to schedule periodic stress tests for collaborators, who provide short voice samples that are analyzed automatically. The model used in the application was selected after benchmarking more than 60 machine learning algorithms with the LazyPredict framework, trained on a dataset collected from real users.

The contributions of this work are: (i) the creation of a novel dataset specifically designed for work stress detection through voice; (ii) a systematic methodology for model selection and evaluation using the LazyPredict framework to systematically assess a wide range of algorithms; (iii) the design and implementation of a scalable microservices-based architecture that integrates mobile development technologies, low-latency APIs, and cloud-based machine learning services to support real-time stress inference; and (iv) the development of a mobile application that enables continuous monitoring and detection of work-related stress using voice input, providing a practical and accessible tool for end users.

The remainder of this paper is organized as follows: Section 2 reviews related work, Section 3 details the methodology and system design, Section 4 presents the results, and Finally, Section 5 concludes with future works.

2 Related Works

This section reviews key literature on stress detection using physiological signals, acoustic biomarkers, and machine learning. A Directed Literature Review (DLR) was conducted to ensure relevance, academic rigor, and minimal selection bias. The search, conducted in Scopus with the search string (“stress” AND (“voice” OR “biomarker” OR “machine learning” OR “detection”) AND “employees”), yielded 40 articles. Inclusion criteria required studies to: (1) use physiological or acoustic signals for stress detection, (2) apply machine learning, and (3) include experimental validation. Exclusion criteria ruled out studies lacking machine learning or technical implementation. After screening, 10 articles were selected for in-depth review and categorized by primary input data type used for stress detection.

2.1 Models Based on Physiological Biomarkers

In [6], researchers evaluated heart sounds from in-ear devices compared to ECG signals, demonstrating that despite motion artifacts, in-ear HRV features processed via machine learning offer a promising non-invasive method for stress detection. Their best-performing model using in-ear data reached 81.1% accuracy, slightly surpassing the ECG-based system (76.5–78.9%). After applying an error-balanced data augmentation strategy to mitigate artifact bias, the model achieved ~77% accuracy, confirming the robustness of the approach for real-world biosignal monitoring. In [11], researchers introduced "Stress-Track," an IoT-based system that integrates body sensors for temperature, sweat, and motion monitoring with a stacked ensemble learning model combining Random Forest and Gradient Boosting. The system achieved 99.5% accuracy, classifying stress into three levels (low, normal, and high) and transmitting data to a cloud-based platform in real time. This work highlights the potential of IoT-connected wearables and multi-sensor fusion as effective, non-invasive tools for preventive stress monitoring in smart healthcare applications. Stress detection based on vocal biomarkers was explored in [8] using the ECAPA-TDNN model with Korean workers, yielding 77.5% accuracy and supporting the use of voice-based monitoring in workplace mental health contexts.

Researchers in [7], developed a smartwatch combining sweat cortisol sensors and HRV, using a hybrid GBM-RF model that achieved 100% accuracy, emphasizing the value of multimodal wearables in real-time physiological stress detection. In [12], researchers used AI-powered entertainment robots with multimodal emotion recognition to provide emotional support to students through adaptive interventions, illustrating the potential of personalized mental health technologies. Finally, in [9], researchers used deep learning models, including LSTM networks, applied to voice data from Indian patients to detect psychological stress, achieving 98% accuracy and demonstrating the method's applicability in low-resource clinical settings.

In summary, physiological and acoustic signal-based models, especially when integrated with IoT and AI, demonstrate high accuracy (often above 98%) and real-time monitoring capabilities. Nonetheless, challenges related to scalability, portability, and accessibility remain barriers to widespread implementation. For instance, scalability issues may arise when multiple users send audio samples simultaneously, potentially saturating the backend infrastructure. Portability is also a limitation, as performance may vary depending on the hardware capabilities of different mobile devices. Finally, accessibility remains a concern, since current solutions are primarily designed in a single language and may not adequately address the needs of users with hearing impairments or other disabilities.

2.2 Models Based on Acoustic Signals and Machine Learning

Researchers in [13] validated a machine learning–based respiratory-responsive vocal biomarker (RRVB) initially trained on voice samples from 1,700 asthma patients and healthy controls. The same model was tested on new data from patients with COVID-19, COPD, and other respiratory conditions recorded through smartphones. Using Logistic Regression on a 6-second sustained vowel ("ahh"), the model achieved 73.2% sensitivity and 62.9% specificity in distinguishing COVID-19 patients from healthy individuals. Results confirmed that acoustic features of the voice can serve as non-invasive indicators of respiratory impairment across diseases, languages, and geographic settings. Similarly, in [14] the researchers applied machine learning techniques to multiple non-invasive physiological signals—including ECG, EMG, GSR from the hands and feet, and respiration—to detect stress in car drivers. Their proposed AI-based Driver Assistance System (AI-DAS) followed a three-phase process of preprocessing, feature extraction, and classification using data from the drivedb dataset. Among several tested models, the Random Forest classifier achieved the best performance, reaching 98.2% accuracy, 97% sensitivity, and 100% specificity. The study demonstrates the effectiveness of multi-sensor integration and machine learning for real-time stress detection in dynamic and high-risk environments such as driving.

Voice analysis for early Parkinson's detection was explored in [15], where researchers used a public dataset of 252 samples and different models. Among these models, KNN, SVM, AdaBoost, ANN, and KDE, KNN performed best with 98.52% accuracy, supporting the use of vocal biomarkers and ML for non-invasive, cost-effective diagnosis. A hybrid AI model combining CNN, RNN, MKL, and MLP was also proposed for Parkinson's detection in [16], the researchers used 81 voice recordings and extracting acoustic features such as MFCCs, jitter, and shimmer. The model reached 91.11% accuracy.

In summary, machine learning has shown high potential for early disease detection using non-invasive signals, particularly in conditions like Parkinson's and COVID-19. However, stress detection remains relatively underexplored, highlighting a promising direction for future research. Although some of the studies reviewed, such as those focused on Parkinson's disease or COVID-19 detection, do not address stress directly, they were included due to their methodological relevance. These works demonstrate the effectiveness of combining acoustic biomarkers with machine learning for health-related monitoring tasks. Their inclusion provides evidence that the same methodological principles, voice signal processing and predictive modeling, can be extrapolated to stress detection in remote work contexts.

3 Methodology

This section outlines the proposed methodology for early detection and monitoring of work-related stress using voice analysis. The system is built on a scalable microservices architecture, integrating mobile technologies, low-latency APIs, and cloud-based machine learning. It covers dataset selection, model choice, evaluation metrics, and the system's logical and physical architecture.

3.1 Data Collection

A total of 60 participants (30 men, 30 women) between the ages of 18 and 50 (mean age = 20) were recruited for this study. Participants were categorized into two distinct groups based on their diagnostic status: one group consisting of individuals previously diagnosed with work-related stress, and a second group of individuals with no such diagnosis.

The dataset was constructed through a structured process involving data acquisition, labeling, preprocessing, and feature extraction. Voice samples were acquired using the WhatsApp messaging application. Participants were instructed to record an audio sample of approximately 15 seconds, prompted by either reading a short text or answering a simple question. Each collected voice recording was subsequently labeled according to the participant's self-reported emotional state at the time of the recording. This procedure yielded a dataset of 65 Spanish-language voice recordings, categorized as either “stressed” (n=29) or “not-stressed” (n=36).

The raw audio files were initially stored in the “.opus” format, which necessitated their conversion to the .wav format to ensure compatibility with the selected audio processing libraries. Following this conversion, an acoustic feature extraction process was performed to derive key biomarkers from each signal. The following 15 features were extracted based on [17] and [18]:

- The first 13 Mel-Frequency Cepstral Coefficients (MFCCs)
- Pitch, representing the fundamental frequency of the voice
- Root Mean Square (RMS) energy, as a measure of audio intensity

The selected features represent key acoustic correlates of stress: spectral content, pitch, and intensity. The final dataset includes 16 columns: 13 MFCCs, pitch, RMS, and a binary class label (stressed/not stressed). We applied standardization due to the differing value ranges.

3.2 Model Selection

To select the best model for detecting work-related stress from voice data, we used LazyPredict, which automates training and evaluation of multiple classifiers, reporting metrics like accuracy, F1-score, and execution time.

For robust model validation, particularly given the limited size of our dataset, we implemented a Leave-One-Out Cross-Validation (LOOCV) strategy. LOOCV is highly effective for small datasets as it maximizes the utilization of available data for training in each iteration, thereby providing a nearly unbiased estimate of model generalization performance. This technique obviates the need for a static train-test split by iteratively using each data point once for testing while the remaining data serve as the training set. The comprehensive results of this systematic model comparison are presented in Table 2. Based on the initial evaluation in Table 1, the top five models selected for further analysis were: (i) DecisionTreeClassifier, which builds predictive models using hierarchical decision rules; (ii) LinearSVC, a linear classifier that maximizes the margin between classes; (iii) LogisticRegression, which estimates binary outcome probabilities from predictors; (iv) Perceptron, a basic neural network for binary classification; and (v) RidgeClassifier, which applies ridge regression followed by thresholding to classify. Among these five candidates, the DecisionTreeClassifier demonstrated the superior performance in the comparative analysis, establishing it as the most promising model for this application.

Table 1. Results of the Top 5 Models Obtained with LazyPredict

Model	Accuracy	F1 Score	Time Taken
DecisionTreeClassifier	0.66	0.66	0.03
LinearSVC	0.66	0.66	0.02
LogisticRegression	0.65	0.65	0.04
Perceptron	0.63	0.63	0.03
RidgeClassifier	0.62	0.62	0.02

3.3 Evaluation Metrics

The model was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. An exhaustive hyperparameter search was conducted for each of the five candidate models using GridSearchCV, with Leave-One-Out (LOO) cross-validation as the evaluation strategy. LOO, where each sample is used once as a validation fold, is well-suited for small datasets and provides robust performance estimates. The specific hyperparameters and their search spaces are shown in Table 2.

Table 2. Hyperparameters of the Top 5 Models

Model	Parameters
DecisionTreeClassifier	criterion, max_depth, min_samples_split
LinearSVC	C, loss, max_iter
LogisticRegression	C, penalty, solver
Perceptron	penalty, alpha
RidgeClassifier	Alpha

This tuning process allowed for the identification of optimal combinations in terms of accuracy and efficiency.

Table 3. GridSearchCV Results

Model	Accuracy	Precision	Recall
DecisionTreeClassifier	0.75	0.75	0.75

LogisticRegression	0.67	0.67	0.67
LinearSVC	0.66	0.66	0.66
Perceptron	0.65	0.65	0.65
RidgeClassifier	0.62	0.62	0.62

The Table 3 shows the results of the hyperparameter optimization process, confirmed the superiority of the DecisionTreeClassifier. This model achieved the best overall performance, demonstrating a balanced accuracy, precision, and recall of 0.75. This peak performance was obtained with the following hyperparameter configuration: a criterion of 'gini', a max_depth of 2, and a min_samples_split of 2.

The DecisionTreeClassifier markedly outperformed the other candidate models. In descending order of performance, the subsequent classifiers were LogisticRegression (0.67), LinearSVC (0.66), and Perceptron (0.65). The RidgeClassifier yielded the lowest performance among the top five, with a score of 0.62.

This outcome underscores the efficacy of hyperparameter optimization and solidifies the choice of the DecisionTreeClassifier as the definitive model for this application.

3.4 Logical Architecture of the Application

Figure 1 presents the logical architecture of the mobile application, which outlines the system's components organized into four primary layers.

The Client Layer encompasses the mobile interface and defines two user roles: (i) Collaborators, employees who perform stress tests scheduled by a leader, and (ii) Leaders, who manage teams, invite collaborators, schedule weekly tests, and access historical results. If a collaborator records a "stressed" result three consecutive times, the system automatically alerts the leader. Inputs at this layer are user actions such as logging in and recording voice samples; outputs are data payloads (audio file, user ID, and authentication token) transmitted to the backend.

The Service Layer acts as the API gateway, receiving requests from the client, validating tokens, handling errors and logs, and passing authenticated data to the Business Logic Layer. For validation, it communicates with the User Database to confirm active sessions and retrieve user details.

The Business Logic Layer executes the core processing pipeline: (i) audio feature extraction (MFCCs, pitch, RMS), (ii) inference with the deployed Decision Tree model, (iii) binary stress classification (stressed / not stressed), and (iv) generation of tailored recommendations. Outputs include the classification result and feedback messages, while interactions with the Data Layer ensure that audio files are stored in the Voice Database and results in the Results Database.

Finally, the Data Layer (Persistence Layer) provides structured storage through three repositories: the User Database (accounts, roles, leader–collaborator mappings), the Voice Database (raw audio samples with metadata), and the Results Database (classification outcomes linked to users and timestamps). This layer guarantees secure and persistent access to historical records for both collaborators and leaders.

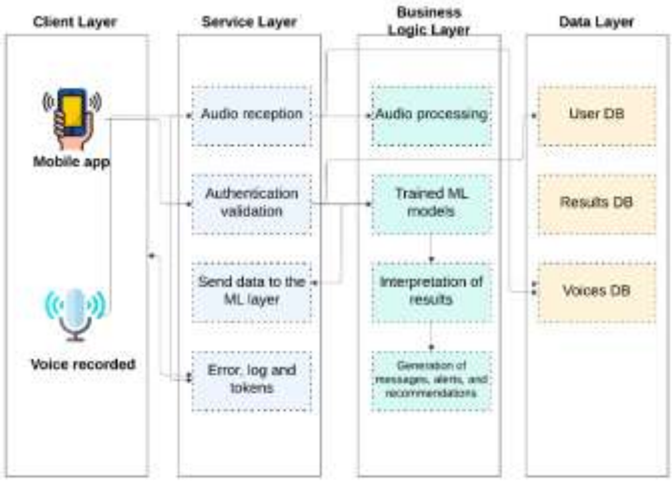

Figure 1. Logical Architecture of the Application

3.5 Physical Architecture of the Application

The Figure 2 shows the physical architecture of the application, designed to support a responsive and scalable real-time stress detection system. The user interaction is managed through a mobile application developed using the Flutter framework, which provides the interface for collaborators to record short audio clips.

Once captured, these recordings are transmitted via the internet to the backend infrastructure. This backend is built upon FastAPI [25], a modern web framework selected specifically for its high-performance asynchronous capabilities, seamless integration with machine learning models, and automated API documentation support. For data persistence, the system utilizes a PostgreSQL database, chosen for its robustness, native support for complex data types, and demonstrated reliability in digital health applications [26].

The core machine learning inference is handled by a dedicated service deployed on Amazon SageMaker. The workflow is orchestrated by the FastAPI backend that upon receiving an audio file, it forwards it to the Amazon SageMaker service. The deployed model processes the data, returns the predicted stress level, and this result is then relayed back through the backend to the mobile application for presentation to the user.

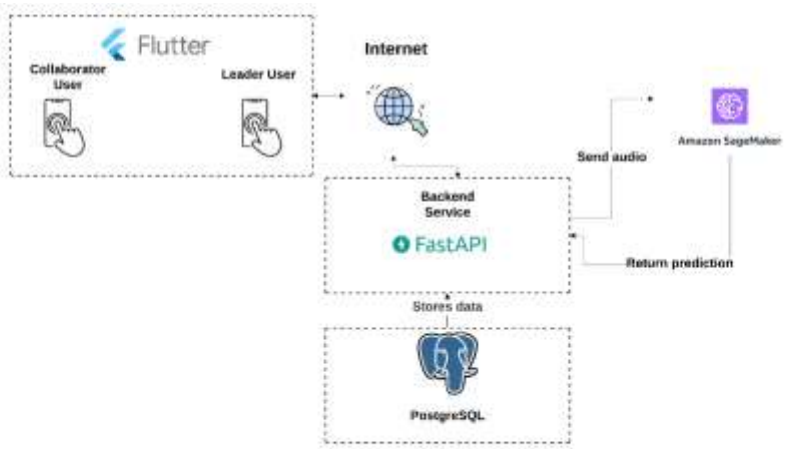

Fig. 1. Physical Architecture of the Application

4 Results

A key outcome of this work is a functional mobile application featuring an intuitive graphical user interface (GUI). The following figures present the main screens of the application prototype, illustrating core functionalities such as user login, audio recording, and the visualization of results and recommendations.

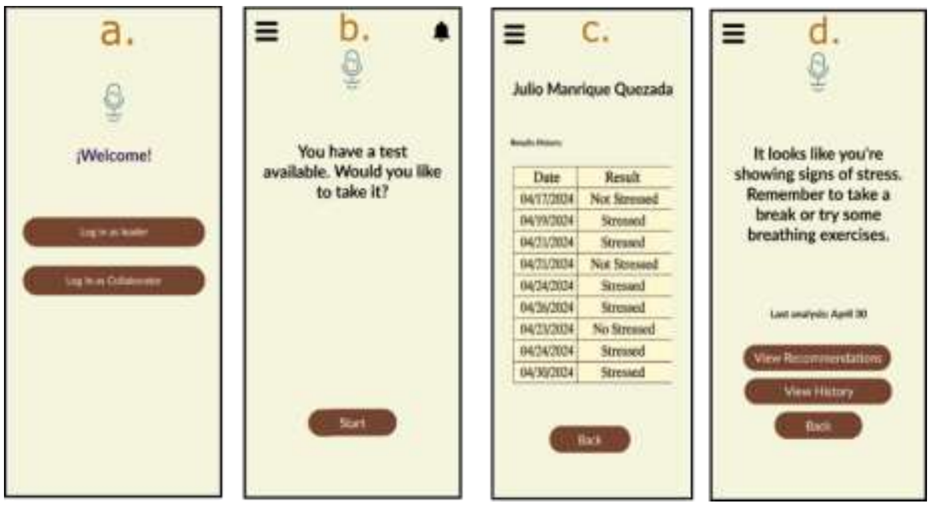

Fig. 3. Collaborator Voice Test Interface

Figure 3 shows the application user interface. The Figure 3(a) shows the Panel of welcome screen, where users select their role: Leader (responsible for managing collaborators and scheduling stress tests) or Collaborator (end-user who performs voice-based assessments). Figure 3(b) illustrates the stress test initiation screen, where collaborators can launch a pending test by pressing Start to begin the voice recording session. Figure 3(c) presents the results history, displayed in a tabular format with date and binary outcome (Stressed or Not Stressed), allowing both leaders and collaborators to monitor stress levels over time. Finally, Figure 3(d) depicts the results screen, which provides the outcome of the most recent analysis. When stress is detected, the interface displays an empathetic message encouraging self-care, along with navigation options: Recommendations, View History, and Back.

The application features a role-based design with two profiles: Leader and Collaborator. Upon login, users access their respective interfaces tailored to their roles. Leaders focus on team management and well-being monitoring, with access to historical stress data for collaborators and the ability to schedule weekly evaluations to foster preventive mental health practices. Collaborators conduct self-assessments by recording a short voice sample, which the system analyzes using acoustic biomarkers (MFCC, pitch, RMS) and a machine learning model to provide near real-time stress predictions. When stress is detected, collaborators receive actionable recommendations such as breathing exercises; if not, they can continue their tasks without interruption.

5 Conclusions and Future Work

This study presents the design, implementation, and validation of an end-to-end system for detecting work-related stress via machine learning analysis of acoustic biomarkers. Using the LazyPredict framework and Leave-One-Out cross-validation, a DecisionTreeClassifier was selected for its balance of accuracy, interpretability, and efficiency, enabling deployment on resource-limited mobile devices.

Our findings confirm that vocal features, MFCCs, pitch, and RMS energy, are reliable stress indicators, achieving 75% balanced accuracy, precision, and recall. This demonstrates the feasibility of objective, non-invasive periodic mental health monitoring scheduled by leaders.

The primary contribution is the integration of an effective predictive model with a functional mobile prototype, bridging theoretical research and practical application. This tool has significant potential in occupational health and telemedicine. An important limitation of this study is that the system does not perform continuous monitoring, but rather periodic assessments scheduled by leaders. This discrete approach may restrict its applicability for certain categories of remote workers, for example, professionals such as software developers who may not use their voice regularly while working. Moreover, since the tests are scheduled in advance, there is a potential risk of result manipulation, as individuals could alter their vocal patterns before a test (e.g., through medication or alcohol). These factors highlight the need for future work to explore more naturalistic and unobtrusive methods of stress detection, potentially through multimodal monitoring that integrates both acoustic and physiological signals. Future works includes expanding the dataset for improved generalizability, exploring deep learning architectures like CNNs or Transformers for enhanced feature extraction, and developing a multimodal system by combining vocal biomarkers with physiological signals from wearables to improve detection accuracy. Future evaluations should also incorporate user studies to assess perceived usefulness, acceptance, and ethical considerations of voice-based stress monitoring in remote work environments.

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