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Multimodal Approaches of Mental Stress Detection: A Comparative Study

Senthil Kumar T ,Vedant Kolhe,Rithvee Chandak
Department of Computing Technologies SRM University of Science and Technology Chennai, India

Abstract- Recently mental health has been regarded as an important issue with stress being one of the factors behind many health conditions. Prompt detection of mental stress is critical in preventing chronic conditions. Artificial intelligence has been helping to fight against chronic stress and tension. This study provides a review of the current understanding of stress and artificial intelligence as well as the approaches for overcoming it with AI algorithms. Some of the approaches studied in development include LSTM networks self-organizing maps and natural language processing applied to datasets. The comparative analysis of these methods enables us to determine the most successful approaches their limitations and ways in which they can be improved.

Keywords- stress detection multimodal approaches com- parative study.

I. INTRODUCTION

”In psychological sciences stress is a feeling of mental press and tension” [1].Stress is the major issue peoples face which is mostly because of work pressure personal responsi- bilities and digital lives. When a person have stress from long time and not managed properly it can have the bad effects on both physical and mental health leading to problems like anxiety depression heart disease and a weak immune system [2]. In many cases stress goes unnoticed until it increases into more serious health problems. This project aims for early detection which is necessary for effective intervention and prevention. While traditional stress management methods depends heav- ily on clinical tests recent achievement in artificial intelligence and machine learning have opened up new possibilities for real- time stress detection. By analyzing physiological data from wearable devices [3] behavioral patterns from smart- phone usage and social media interactions AI models can offer continuous stress monitoring.

However there are challenges which stays regarding privacy and data accuracy. This project focuses on comparing various AI methods for detecting mental stress evaluating the strengths and weaknesses of different machine learning models and techniques. Also this shows how each method identifies stress across various data sources including physiological signals behavioral patterns and social media content. The goal is to find the most effective and real time solutions for stress detection. This effort is important as it helps in building the foundation and improving mental health monitoring and management systems.

II. FACTORS INFLUENCING STRESS

Stress indicators are mostly divided into physical emo- tional and behavioral signs that shows when an individual is under stress [4]. These indicators mostly varies from physical symptoms like fatigue restlessness and muscle tension also emotional reactions such as irritability and anxiety. According to Dr. Deepti Bhargava and Hemant Trivedi’s study on youth stress key reasons for stress in students includes academic pressure and peer expectations [5]. In day-day environment stress leads to decreased in productivity which further shows the wide impacts of stress across different life domains .Several factors determining stress includes academic challenges family issues and social support.

Academic Stress

Academic stress is one of the most significant contributors particularly in students. Pursuing higher education has always been considered to be stressful as students need to adapt to new social and academic environment [6]. The study by Haiying Wang and colleagues found that mastery oriented goal setting where students focus on learning and personal growth rather than performance alone helps reduce stress and improve academic management [7].

Family Functioning and Social Support

Family functioning and social support are critical in man- aging children stress. As per Xinquan Huang et al.’s study children with strong family bonds and positive relationships shows lower levels of depression and stress which further

shows the protective role of family and social networks in emotional well-being of child [8].These shows the importance of supportive family helps in development of a child.

Music Therapy

Music therapy has been highly researched as a tool for stress management. Jacqueline LaRivee's review on the neuro-scientific and clinical applications of music found that music therapy can activate the brains relaxation response also lowering stress hormones and promoting emotional regulation [9]. Rishav Bharadwaj study on university students also shows that music therapy reduced anxiety and stress among participants proving effective across different age groups and contexts [10] . The variation in the types of music used plays a role in how effective this therapy is which further shows the most significant reduction in physiological stress markers like heart rate and blood pressure [11].

Work Stress

Work related stress and uncertainties about future careers are also major stressors particularly among young people. Bhargava and Trivedi's study revealed that career uncertainties peer pressure and family expectations contribute heavily to stress in youth [5]. As the demands of academic and professional life grows managing these stressors through time management social support and relaxation techniques becomes important.

III.METHODS OF STRESS DETECTION

Mental stress detection has become a significant area of research because of the increasing concern of stress related issues. Today various methods have been explored to develop accurate real time detection systems using physiological behavioral and emotional data. These methods shows the power of artificial intelligence and machine learning to analyze a wide range of inputs from body signals to digital footprints and provide early warnings of stress levels. This section shows the primary methods for stress detection and how we can analyze it further it also analyzes strengths and weakness. Taking into account the comparative analysis of different machine learning models we conducted detailed research over publicly accessible datasets. We noticed there were 50 to 60 papers focusing on mental stress detection and we incorporated these datasets into our analysis. This enabled us to broaden the dataset collection and include datasets from different scenarios populations and stress detection methods. We were able to focus our analysis on current research trends while broadening the scope of evaluation by utilizing datasets previously already used in other studies. The incorpo- ration of papers from different research areas helped us further strengthen our comparison of the machine learning models by enabling us to test the models on different types of data – physiological data speech and even text. The incorporation of various datasets from controlled environments to more open real-world data made our results more reliable and provided a balanced assessment on the models performance on different stress-inducing scenarios.

Physiological Data Analysis

One of the approaches for stress detection is analyzing physiological data of wearable devices [3] [12] with the help of sensors devices such as smartwatches and fitness trackers collect data from the user which further includes heart rate signals electrodermal activity galvanic skin response respiration rate and blood pressure [12]. These signals shows the direct reflection of the body in case of stress. Machine learning models such as Long Short Term Memory networks [13] Support Vector Machines and Random Forests are often applied to this physiological data to analyze stress levels with high to moderate level of accuracy. By using time series analysis and LSTM models it helps predicting accurate and effective tracking changes in physiological signals over time though their performance which further can be influenced by noise or variability in sensor data.

Behavioral Data from Smartphones and Activity Tracker

Here data from smartphone users based on their behaviour and physical activity is been taken also various fitness trackers plays a significant role in stress detection. Patterns such as frequency of calls texting habits app usage screen time and even data location can provide indirect clues about a users mental state. Studies have shown that individuals experiencing stress may have altered sleep patterns reduced physical activity or increased phone usage [14] [15]. Machine learning models like Random Forests Decision Trees and K-Nearest Neighbor have also been applied to behavioral data for stress detection [16]. These models can detect stress by identifying different activities from normal behavior offering a non invasive methods of monitoring mental well being. Behavioral data when combined with physiological data enhances the accuracy of stress detection systems by providing a proper approach for early detection.

Social Media and Text-Based Analysis

The hype of social media has provided us with new data source for detecting stress through textual analysis. Natural Language Processing techniques which includes sentiment analysis are been applied to social media posts comments and messages to detect stress related issues [17]. For example by analyzing the language used in tweets or facebook posts researchers can identify level of anxiety frustration or other stress indicators. Naive Bayes support vector machines and LSTM models are often employed to analyze this text data. LSTM networks plays important role in handling sequential text data making them effective for processing the natural flow of language While text-based analysis provides valuable insights into emo- tional states it can be limited by the quality and quantity of available social media data as well as users willingness to share personal experiences online.

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Speech Signal Analysis

Speech patterns help in offering another valuable data for stress detection [18]. By analyzing personal features of a person like tone pitch and pauses in speech AI models can analyze emotional changes that help to detect stress. The human voice is a rich source of information about its own psychological state.

Markov Models are commonly used for speech analysis. These models are capable of analyzing patterns in vocal data that are typical of stress offering non-invasive and accessible methods of stress detection. Speech analysis also requires high-quality audio input and can be influenced by environmental noise which is a challenge in real-world applications.

Self-Organizing Maps (SOM) and Unsupervised Learning

There are some situations where the labeled data is short then the self-organizing maps and other unsupervised learning techniques provide a useful approach to stress detection. SOMs groups unlabelled physiological or behavioral data into patterns that may indicate stress without the need for any predefined labels. This helps to show the hidden parts in complex datasets which provides useful information about stress levels without any external use of training data [19].

Unsupervised learning techniques such as K-Means Clustering and Principal Component Analysis are also present there to identify stress-related issues in data While these models are useful for exploring unknown patterns their dependency on grouping can sometimes produce less accurate predictions compared to supervised learning methods. However they have a valuable tool in the early stages of stress detection model development.

Ensemble Methods

Ensemble methods such as gradient boosting and random forest ensembles help mitigate the limitations of individual models by reducing bias and variance. Combining these tech- niques with time-series models like LSTM networks further enhances the system's ability to detect stress in real-time making it a promising approach for personalized and adaptive stress management solutions.

Emotion Detection via Facial Expressions

In physiological and behavioral data there are some approaches which focus on detecting stress through facial expressions [20]. Using facial recognition technology stress can be identified by micro expressions and muscle movements which often shows the persons emotional states.

Convolutional Neural Networks and deep learning models are commonly used for this type of analysis. These models is right for recognizing facial patterns and changes making them highly effective for emotion and stress detection. However in real world uses of facial recognition-based stress detection faces privacy concerns.

IV. COMPARISON OF MACHINE LEARNING ALGORITHMS

Long Short-Term Memory

Accuracy percentage is 90-95%. The type of dataset is a primarily time series data from physiological signals . They are mostly collected from wearable sensors.The strengths of LSTM is the ability to capture temporal dependencies makes LTSM ideal for analyzing continuous physiological data streams as stress fluctuates over time.The main weakness of LSTM is that it is less effective with non-sequential and small datasets.

Random Forest

Accuracy level is 80-90%. Dataset used Works well with both structured datasets from physiological and behavioral data for example sleep patterns physical activity and phone usage patterns. Also can handle many data combining various stress indicators.The strengths of random forest is it handles high dimensional data and is effective with both time series and non sequential data.Weakness of random forest is that it is less effective for real time data and may struggle with datasets involving sequential patterns compared to models like LSTM.

Support Vector Machine

Accuracy level is 75-88%. Dataset type used is with physiological data like HRV and EDA also speech data like voice pitch and tone. Also applied to behavioral data that is smartphone usage patterns. Strengths of SVM is that it excels in binary classification and is effective when the dataset is well structured and of small sized. It is less suitable for very large and noisy datasets and is not ideal for time series data unless it is appropriately preprocessed.

K-Nearest Neighbors

Accuracy level is 70-85%. Dataset comprises small struc- tured behavioral data like smartphone usage and physical activity levels where real time processing is not required.It performs well on small datasets and is simple to implement but struggles with large and noisy datasets leading to lower accuracy.

Na¨ıve Bayes

Accuracy level is 70-80%. It is best suited for text data from social media posts where it can classify sentiment or emotion as well as small behavioral datasets. It works well with small text datasets for sentiment analysis and is fast to compute. The only weaknesses is that it assumes feature independence limiting accuracy with more complex or interrelated data.

Decision Trees

It has an accuracy level of 75-85% with behavioral data (e.g. phone usage patterns sleep data) as well as physiological signals in some cases. It is easy to interpret and works well with structured datasets .However it is less effective with noisy or sequential data.

Convolutional Neural Networks

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Accuracy level is 80-90%. It works best with image data and audio data typically collected from facial recognition systems or speech analysis tools. Strengths include excellent for identifying stress through visual and auditory cues by learning patterns in the data .However it requires large labeled datasets for training and is computationally expensive.

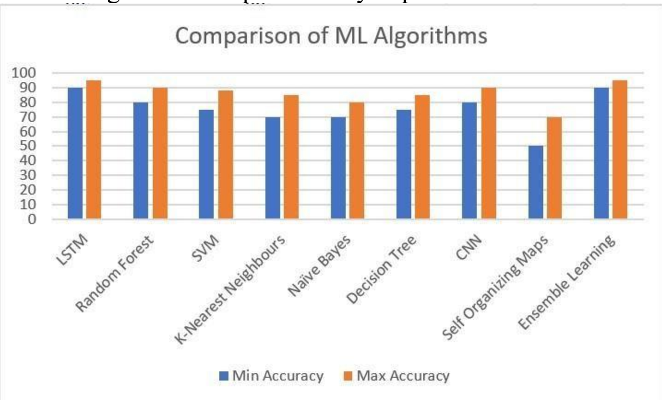

Figure. 1. Comparison Chart

Self-Organizing Maps

Accuracy level is typically below 70%. It is used for unlabeled datasets or unsupervised learning scenarios ex- ploring hidden patterns in physiological or behavioral data .It is suitable for exploratory analysis and clustering when labeled data is unavailable. Weaknesses include Low accuracy compared to supervised models and it struggles with real-time stress detection.

Ensemble Learning

Accuracy level is 90-95%. It can handle multimodal datasets from both physiological behavioral and textual data sources. It combines wearable sensor data with behavioral patterns or social media data.

V. FINAL RESULT

By combining different models ensemble methods capture diverse stress indicators and achieve high accuracy. However computationally intensive and complex to interpret requiring large labeled datasets for training.

The choice of machine learning model for stress detection depends largely on the type of dataset. While LSTM is most effective for time-series data from physiological sensors achieving high accuracy by capturing temporal patterns ran- dom forest and ensemble methods perform well on structured and multimodal datasets. Models like Na¨ıve Bayes and SVM are better suited for textual or smaller datasets though their performance is lower for complex data. Hence combining multiple models with diverse data sources in a hybrid or ensemble approach yields the highest accuracy for stress detection.

VI. CONCLUSION

This project shows a complete comparison of different machine learning models for mental stress detection which includes LSTM Random Forest SVM Naive Bayes Decision Trees CNN and ensemble learning methods. Through this analysis it becomes clear that different models shows different levels of accuracy depending on the dataset used and the features of the data.

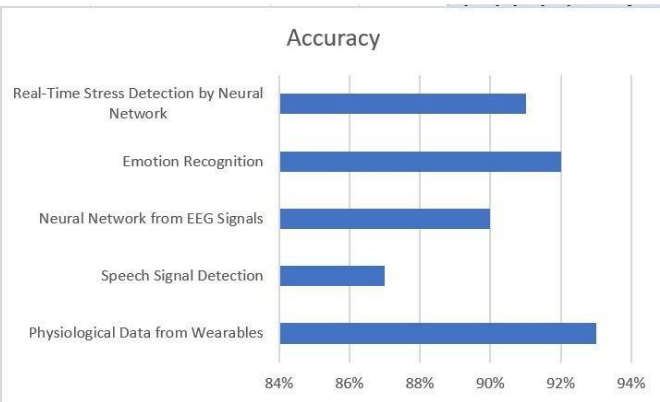

Figure. 2. Versatility of LSTM in the following area.

LSTM takes a advantage in processing time series physio- logical data which makes it good for real time stress detection through wearable devices. Ensemble learning methods achieve the highest accuracy which is 90-95.

However no single model provides perfect accuracy and performance across all stress detection methods and the project identifies several opportunities for further research. Combining models integrating multimodal data and optimization for real time applications remain promising to enhance stress detec- tion systems. By integrating more highly developed machine learning techniques and addressing the ethical implications of data use this project lays the foundation for future advances for the accurate real-time detection of mental stress.

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