COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR HUMAN STRESS LEVEL PREDICTION: PERFORMANCE METRICS AND INSIGHTS

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ABSTRACT

In this review study, several machine learning models that are used to predict human stress levels are thoroughly analyzed, with a particular emphasis on Random Forest (RF), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks. The design, benefits, limitations, and performance measures of each model are thoroughly examined to provide a comprehensive understanding of their capabilities. Known for its ensemble learning methodology, Random Forest constructs several decision trees to improve precision and robustness. Even though its astounding accuracy rates, which range from 72% to 95%, can be challenging to interpret and computationally demanding, especially in vital industries like healthcare. However, with accuracy rates ranging from 79% to 95%, SVM is acknowledged for its efficiency in managing high-dimensional spaces and complicated datasets. Nevertheless, it is sensitive to feature scaling and can yield difficult-to-interpret complex decision limits. On the other hand, LSTM networks are especially well-suited for stress prediction from time-series data since they are expressly made for sequence prediction tasks and are excellent at capturing temporal relationships in data. LSTM models have proven to be remarkably effective, with accuracy reaching 99.71%. However, their usefulness in real-time scenarios may be limited because to their requirement for substantial processing resources and a huge volume of labeled data for effective training. All in all, these models' performance measures highlight how successful they are at predicting stress, with RF, SVM, and LSTM each having particular advantages and disadvantages. This study offers insightful information for academics and practitioners in the subject of stress analysis, emphasizing the significance of choosing the right model depending on particular requirements.

Keyword: - *Machine Learning, Stress Prediction, Random Forest, Support Vector Machine, Long Short-Term Memory*

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1. INTRODUCTION

Predicting human stress has grown in importance as a field of study, especially in light of the increased awareness of its effects on health and wellbeing [1]. To efficiently predict stress levels based on physiological, behavioral, and environmental data, a number of machine learning models have been created. The Random Forest classifier, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) networks are three of these models that have gained prominence and each has its own advantages and disadvantages [2][3][4]. By utilizing various algorithms and architectures, these models are able to examine intricate information, providing academics and practitioners with valuable insights into stress dynamics and the improvement of therapies.

As an ensemble learning technique, the Random Forest classifier improves accuracy and robustness by aggregating the predictions of several decision trees. SVM, on the other hand, works well with high-dimensional data since it concentrates on identifying the best hyperplane to divide classes. Recurrent neural networks, such as long short-term memory (LSTM) networks, are especially well-suited for time-series analysis in stress prediction because of their superior ability to handle sequential data and capture temporal dependencies. This paper explores the features, limitations, and performance measures of these three models, emphasizing their contributions to the field of human stress prediction and offering a thorough analysis of their suitability in different scenarios.

2. RANDOM FOREST CLASSIFIER

One of the most well-known machine learning methods for estimating human stress levels is the Random Forest (RF) classifier. By merging the predictions of several decision trees, this model functions as an ensemble learning technique that improves overall resilience and accuracy [5].

2.1 Architecture

As the model's foundational learners, Random Forest builds a large number of decision trees—usually hundreds to thousands. Instead of analyzing every feature that is accessible, RF uses an approach during the tree-building process where it randomly chooses a subset of features to take into account at each split. This method increases model variety while lowering tree-to-tree correlation. To train each tree on a random subset of the training data, RF uses bagging. By using sampling with replacement, this strategy makes it possible for the training datasets for each tree to vary. In classification problems, the Random Forest model's final output is decided by a majority vote across all individual trees' predictions, which aids in stabilizing the forecast as a whole.

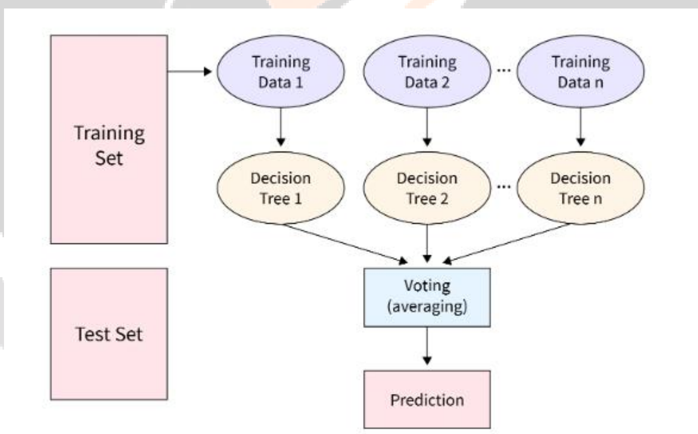

Fig -1: Architecture of Random Forest Classifier

2.2 Drawbacks of Random Forest Classifier

Training a large number of trees can be computationally intensive, particularly with large datasets. This can lead to longer training times and increased resource consumption. It can take a lot of computing power to train a lot of trees, especially for big datasets. Longer training sessions and more resource usage may result from this. Although RF can be used to determine the significance of a feature, the intricacy of each decision tree makes it challenging to understand the model as a whole. This is especially true in industries like healthcare, where it's critical to comprehend the decision-making process. In datasets where one class is considerably underrepresented, Random Forest may perform poorly. Predictions that are skewed toward the dominant class may result from this.

2.3 Results
Impressive performance metrics have been shown by Random Forest in applications for predicting human stress. With precision values ranging from 81% to 96%, reported accuracy scores normally fall between 72% and 95%. F1-scores vary from 77% to 96%, while recall scores typically lie between 75% and 96% [6]. These measures demonstrate the model's capacity to generate trustworthy forecasts in a range of scenarios, which makes it a top option for stress analysis practitioners and academics.

3. SVM (SUPPORT VECTOR MACHINE) MODEL
A popular supervised learning model for classification applications, Support Vector Machine (SVM) is capable of predicting human stress levels among other things. SVM is well-known for its capacity to handle complex datasets and is especially useful in high-dimensional domains[7][8].

3.1 Architecture
The goal of SVM is to locate the ideal hyperplane in the feature space that divides various classes. The support vectors dictate where this hyperplane will be located. The data points that are closest to the hyperplane and affect its orientation and position are these ones. In order to optimize the margin between the classes, the SVM algorithm concentrates on these points. Classes that are not linearly separable in the original space can be separated thanks to SVM's use of kernel functions to transform the input data into a higher-dimensional space. Radial basis function (RBF) kernels, polynomial, and linear kernels are examples of common kernel functions.

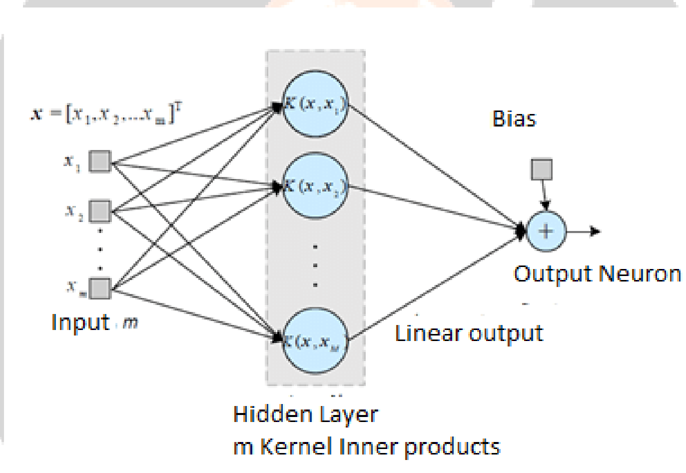

Fig -2: Architecture of SVM model

3.2 Drawbacks of SVM model
SVM is sensitive to the scale of the input function. If the function is not standardized, this could lead to non -optical performance. The decision boundaries produced by SVMs can be complex, making the model's predictions difficult to interpret, and building SVM models can be computationally expensive, especially when using large datasets. The time complexity increases with the number of samples, which may limit scalability.

3.3 Results
The support vector machine (SVM) is an effective model for predicting human stress levels, with performance varying across studies. Accuracy rates range from 79% to 95%, and precision rates range from 75% to 94%. Recall values are typically between 75% and 95%, and F1 scores range from 77% to 94%. These metrics indicate the effectiveness of SVM, but performance can be highly dependent on the dataset and implementation.

4. LONG SHORT-TERM MEMORY NETWORKS (LSTM)
Recurrent neural networks (RNNs) of the LSTM type function especially well for sequence prediction issues. Because of its ability to capture temporal dependencies well, it can be used to forecast stress from time-series data [9][10].

4.1 Architecture

Long Short-Term Memory (LSTM) networks are specifically intended to handle long-term dependencies in sequential data through their architecture. The memory cell, which retains information for lengthy periods of time, is the central component of the LSTM. Three essential gates are part of the architecture: the input gate, which manages how much new data is added to the memory cell; the forget gate, which controls what data should be removed from the memory cell; and the output gate, which chooses which data from the memory cell is sent to the following layer [11][12]. A sigmoid activation function is used by each gate to choose whether values to update, ignore, or output. Because of the complex interplay between the gates, LSTMs are especially well-suited for tasks involving sequential data, like time series prediction, speech recognition, and natural language processing. They can also be used to selectively store, update, and retrieve information, which helps them overcome the vanishing gradient issue that traditional Recurrent Neural Networks (RNNs) frequently face.

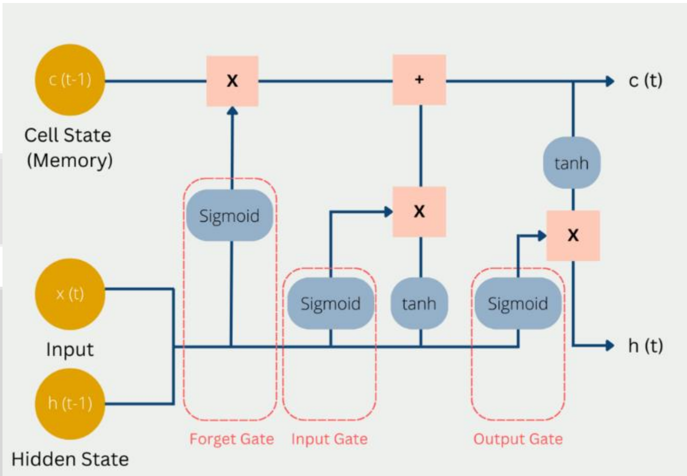

Fig -3: Architecture of LSTM

4.2 Drawbacks of LSTM

Although they are useful in forecasting human stress levels, Long Short-Term Memory (LSTM) networks have a number of disadvantages. Initially, their computing demands can be high, necessitating substantial time and resources for training, particularly with extensive datasets. This could potentially restrict their applicability in real-time scenarios. Second, incorrect settings can result in subpar performance because LSTMs are sensitive to hyperparameter adjustment. Furthermore, overfitting can be a problem for LSTMs, especially when they are trained on tiny datasets, which can limit their generalizability. The intricacy of the model may further complicate the interpretation of the findings, impeding comprehension in crucial domains like mental health. Finally, large volumes of labeled data are necessary for LSTM performance and may not always be available in stress prediction settings.

4.3 Results

In an effort to anticipate human stress levels, Long Short-Term Memory (LSTM) networks have been the subject of numerous studies. Phutela et al. used a two-layer LSTM model using raw EEG signals to achieve an accuracy of 99.71% [13]. Using multimodal data, Umematsu et al. demonstrated considerable improvements in prediction accuracy for students' daily life stress levels [14]. A two-layer LSTM model outperformed a single layer by roughly 20%, according to Sundaresan et al.. Acikmese and Alptekin predicted stress levels by combining LSTM with passive mobile sensors [15]. Furthermore, LSTM has demonstrated its efficacy in stress prediction with accuracy, precision, recall, and F1-scores of 75.54%, 74.26%, 72.99%, and 74.58%, respectively, according to a study published in PMC.

5. CONCLUSION

In summary, machine learning models that have demonstrated promising results in forecasting human stress levels include Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory Networks (LSTM). High accuracy, precision, recall, and F1-scores are attained using Random Forest, although it can be computationally expensive and difficult to interpret. SVM is adaptable and efficient in high-dimensional domains, but it is hard to comprehend and sensitive to feature scaling. Although huge amounts of labeled data are required, LSTM can be computationally costly and sensitive to hyperparameters. It also excels at capturing temporal dependencies in sequential data. The application's particular needs, including those related to accuracy, interpretability, and computational restrictions, will determine which model is best. All things considered, these sophisticated machine learning methods show promise for improving stress management and prediction; however, more study is required to maximize their effectiveness and overcome their drawbacks in practical applications.

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