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Comparison of Machine Learning Models for Stress Detection from Sensor Data Using Long Short-Term Memory (LSTM) Networks and Convolutional Neural Networks (CNNs)

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Abstract

Stress has become one of the serious concerns in modern society and affects health, both mentally and physically, influencing productivity and quality of life. Chronic stress has grave health consequences, including cardiovascular diseases, anxiety, depression, and suppression of immune responses. Early detection and management are thus of utmost importance for mitigating its adverse effects. The increased popularity of wearable devices and physiological sensors now allows the detection of stressors using real-time data. The presented research is targeted at the study and comparison of the performance of two leading deep learning architectures: LSTM networks and CNN, based on stress detection according to physiological sensor data.

This research is based on a dataset of three important physiological parameters: Heart Rate Variability, Galvanic Skin Response, and Skin Temperature, recorded using wearable devices. All these data are filtered for noise and normalized for quality and consistency. In this paper, LSTM and CNN models have been designed, trained, and tested on the same datasets so that a fair comparison can be performed. Accuracy, precision, recall, F1-score, and computational efficiency were the metrics considered to evaluate the model's effectiveness.

These results emphasize the fact that LSTM networks outperform CNNs in terms of extracting temporal dependencies in time-series data, yielding high accuracy, recall, and F1-score. This underlines the fact that LSTMs are much more appropriate in applications such as detection of stress, which requires the deeper understanding of sequential patterns. On the other hand, CNNs do have more computational efficiency and multi-dimensional feature extraction capability, useful in cases where real-time performance is required using limited resources.

This comparative analysis not only points out the trade-offs of the two models but also serves as a pointer to the potential hybrid approaches which integrate the strengths of LSTM and CNN architectures. The findings of this study give practical insights to the researchers, developers, and practitioners in the domain of health monitoring and stress detection. It therefore enhances the knowledge to date on the ability and limits of the models in the general domain of the application of machine learning in mental health, hence more accurate, scalable, yet efficient automatic stress detection systems are enabled.

Keyword: Stress detection, machine learning, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), physiological signals, wearable sensors, Heart Rate Variability (HRV), Galvanic Skin Response (GSR), Skin Temperature (ST), time-series analysis

Introduction

Stress is a common condition experienced by all categories of individuals. Whereas short-term, or "acute," stress generally serves to sharpen the level of alertness and improved productivity, long-term exposure to, or

"chronic," stress has adverse effects on both mental and physical health. Chronic stress contributes significantly to the global burden of disease, with its involvement in cardiovascular diseases, hypertension, diabetes, anxiety, depression, and weakened immune responses. (Lazarus, 1993; McEwen, 1998). Because of that, the early detection and management of stress is important, not only at the individual health level but also for wide-ranging societal and economic concerns.
Traditional techniques of assessing stress rely on subjective self-reporting using questionnaires and interviews. These methods provide insight into perceived levels of stress; however, they are limited by a number of factors such as recall bias, variability in interpretation, and inability to capture real-time fluctuations in stress (Cohen et al., 1983). Recent developments in wearable devices and sensor technologies have changed the landscape for stress detection, allowing real-time data collection of objective physiological signals. Physiological signals, like Heart Rate Variability, Galvanic Skin Response, and Skin Temperature, are valid indicators of stress since they reflect the activity of the autonomic nervous system and thereby the changes induced by stress. As Shaffer & Ginsberg 2017 note,
The integration of machine learning into stress detection has further accelerated progress in this domain. Machine learning algorithms excel at uncovering patterns within large, complex datasets, making them ideal for analyzing physiological signals (Goodfellow et al., 2016). While traditional ML models like Support Vector Machines and Random Forests have been used in stress detection, the introduction of deep learning models, especially Long Short-Term Memory networks and Convolutional Neural Networks, has opened new avenues for more accurate and robust stress classification.

LSTM networks are a particular type of RNN, especially designed to handle long-term dependencies within sequential data. Unlike other traditional RNNs, LSTMs have memory cells and gating mechanisms in their architecture, by which they learn temporal relations quite effectively and reduce the problem of vanishing gradients from the very beginning (Hochreiter&Schmidhuber, 1997). This property makes LSTMs very useful for time-series analysis, where the understanding of sequential patterns becomes of prime importance. In the detection of stress, LSTMs use temporal changes in physiological signals to identify whether a person is stressed or not with high accuracy. Zhang et al. (2020).

Traditionally, CNNs have been associated with image processing; however, their ability to learn the hierarchical representation of features from raw data has made them increasingly popular for one-dimensional signal processing too. LeCun et al. (2015). This, therefore, places the CNNs at an especially excellent position in the extraction of spatially relevant features that enable efficient classification even under resource-constrained scenarios. Recent studies have shown just how efficient CNNs are in the detection of stress, using raw sensor data in capturing stress-inducing patterns with no extensive preprocessing by Zhao et al. (2019). Although CNN and LSTM represent models that have been individually quite successful in several domains, both have rarely been compared regarding direct performance in the context of stress detection. The present study therefore bridges the literature gap by investigating the strength of these two architectures in dealing with physiological sensor data classification of stresses. Key questions in research that this paper highlights or puts forward are:

- How do the LSTM and CNN models compare in terms of accuracy, precision, recall, and F1-score with respect to the detection of stressors?
- What are the computational trade-offs between the LSTM and CNN architectures, especially for real-time applications of stress monitoring?
- Can insights from this comparison help develop hybrid models that can combine the benefits of both architectures?

These questions will be answered by a systematic analysis performed on a dataset of physiological signals gathered from wearable sensors.
The dataset consists of all the physiological signals, such as HRV, GSR, and ST from both stress and non-stress conditions. Preprocessing is performed to assure the quality of the data by filtering noises and

normalizing the data. To ensure unbiased comparison, the models are trained and tested on the same dataset. The metrics adopted in measuring the performance are the models' accuracy, precision, recall, F1-score, and computational efficiency. This study presents its contribution to this fast-growing area of stress detection by giving a better insight into the capabilities and limitations of both the LSTM and CNN models.
This will also open up possibilities for hybrid approaches that combine the strength of LSTMs in modeling temporal dependencies with the efficiency of CNNs in feature extraction. It is expected that this research will help developers, researchers, and healthcare practitioners in the design of more accurate and efficient stress detection systems that could help improve stress management and promote overall well-being.

Literature Review

Recently, there has been an increasing interest in detecting stress from physiological signals in healthcare, psychology, and human-computer interaction. Technology development, especially wearable sensors, has enabled the monitoring of physiological signals in real time; therefore, new methods have been developed for detecting stressors. Especially, LSTM networks and CNNs have been investigated as the powerful tools of ML/DL for automatic stress detection from those signals. The following section provides an overview of the current literature on the subject, including the main approaches and obstacles that are characterizing the current trends in stress detection using physiological signals with machine learning techniques.

Physiological Indicators of Stress

Stress can be associated with a number of physiological changes, most of which can be measured by various sensors. These physiological responses are primarily controlled by the autonomic nervous system, controlling involuntary functions such as heart rate, skin conductance, and temperature. The monitoring of these signals has become one of the main focuses of recent research in stress detection.

1. **Heart Rate Variability (HRV):**
   HRV measures the variation in time intervals between successive heartbeats, reflecting the balance between the sympathetic and parasympathetic branches of the autonomic nervous system. Low HRV is typically associated with stress, anxiety, and other emotional states, as stress causes an imbalance between the two branches (Shaffer & Ginsberg, 2017). Thayer et al., 2012, identified various studies pointing to the validity of both lab and field/natural conditions as a valid mental stress marker. Due to this feature of being non-obtrusive and easily measurable through all available wearables of heart rate monitors and sensors, much research into physiological markers for automatic stress detection with the use of HRV performs an ECG.

2. **Galvanic Skin Response**
   GSR measures changes in skin conductivity that vary with sweat gland activity. The sympathetic nervous system controls the sweat glands, and stress turns on the SNS, resulting in increased sweating. GSR has been one of the most common methods to assess emotional and physiological stress because it offers immediate feedback about arousal levels (Boucsein, 2012). GSR has been shown by researchers to be very sensitive to stress, with considerable changes being observed to both emotional and cognitive stressors alike. Boucsein et al., 2012, present evidence for this assertion.

3. **Skin Temperature (ST):**
   Changes in peripheral blood circulation due to stress may cause changes in skin temperature, that is, vasoconstriction, bringing down the skin temperature during stressful events, especially in the extremities. Hernandez et al., 2013,Thus, it has primarily been used as an indicative parameter of the stress response of the body. The skin temperature might vary because of factors other than stress; however, skin temperature changes caused by an emotional stimulus are fairly documented, which turns out to be very helpful in detecting stressors within it. Kim & Kwon (2017).

Traditional Machine Learning Methods of Stress Detection

Before the emergence of deep learning techniques, traditional machine learning algorithms were the most sought-after ones when detecting stress from physiological signals. Most of these methods are in obtaining handcrafted features from raw sensor data, which might then be used in training machine learning models on classification tasks. Conventional machine learning techniques include the following: Support Vector Machines, Random Forests, and k-Nearest Neighbors.

1. **Support Vector Machines (SVM):**
   One of the most used methods in the literature for stress classification is SVM. The support vector machine works on the principle of finding that hyperplane which best separates the data of different classes, such as stressed versus non-stressed. Several studies have established the efficiency of SVM on stress detection tasks using HRV, GSR, and ST data. For instance, Subasi 2019 has implemented SVM for the classification of the levels of stress from both HRV and GSR signals. Similarly, the work of Nath et al. (2018) involved several studies related to the classification of stress based on multi-modal physiological signals; their work also gives examples of how SVMs are capable of working with high-dimensional and intricate data.

2. **Random Forests (RF):**
   RF is also one of the most applied methodologies based on ensemble learning that involves the use of decision trees in stress detection. The algorithm for RF creates several decision trees during training and then combines them to increase the model's accuracy by reducing overfitting. Random forests can handle categorical and continuous data, especially in the case of multimodal physiological signals. Liao et al. (2018) classified the stress states using RF on GSR, HRV, and skin temperature data. This work showed the strength of the model in practical applications. The results showed that even when the training data was scarce, RF detected the occurrence of stress.

3. **k-Nearest Neighbors (k-NN):**
   k-NN is a simple yet powerful classifier of machine learning, which assigns a data point to a class by a majority vote of its k nearest neighbors. For stress detection, k-NN has been applied to time-domain and frequency-domain features of physiological signals including HRV and GSR. Though k-NN is easy to use and has little training time, it is inefficient with big data. However, a few works showed that k-NN was able to perform reasonable performance in the classification task of stress and when feature selection methods were combined (Tajaddini et al., 2016). While these traditional machine learning methods have ensured reasonable success in the detection of stress, they are limited by their inability to model the temporal dependencies inherent in physiological signals effectively. These limitations have driven the use of deep learning models, especially the use of LSTM and CNNs.

Deep Learning Models for Stress Detection

Deep learning models, specifically the LSTMs and CNNs, have been in great demand for stress detection in recent years because of their ability to learn complex and non-linear patterns of data without requiring extensive feature engineering. Both LSTMs and CNNs are very effective in processing physiological signals, which are often sequential and high-dimensional in nature.

Long Short-Term Memory Networks

LSTMs are a particular sort of RNN engineered to be able to learn and remember long-term dependencies within sequential data. They have been particularly effective for such time-series classification tasks as stress detection, in which the temporal structure of the data is informative. LSTM networks use a memory cell mechanism that allows them to capture long-range dependencies in the input data, mitigating the vanishing gradient problem that traditional RNNs often face (Hochreiter&Schmidhuber, 1997). LSTM-

based models have been successfully applied to detect stress from physiological signals such as HRV, GSR, and EEG (electroencephalography).
Zhang et al. (2020) used LSTMs to detect stress from wearable sensors that recorded HRV and GSR data. The study showed that LSTM networks captured sequential patterns in the data indicative of stress and hence achieved better classification performance compared to traditional machine learning models. LSTMs are fit for real-time monitoring of stress since they can continuously process the incoming sensor data flow, thus finding their ideal application in dynamic environments characterized by rapidly changing levels of stress.

Convolutional Neural Networks (CNNs)
Those CNNs tended to show high performance, particularly on high-dimensional data, in different complex feature and classification tasks. While they were designed for the treatment of image data, they have more and more frequently been adapted for one-dimensional time-series physiological data. The principal architecture of CNN consists of many convolutional filters consecutively to identify salient features automatically from the input data, joined by pooling layers that diminish the dimensionality and enhance computational efficiency.
Various studies have been done in which CNNs were applied to the task of stress detection, often with results comparable or superior to other machine learning methods.
For example, Zhao et al. 2019 employed CNNs for the purpose of stress detection based on GSR, HRV, and ST data. They demonstrated very high accuracy in the classification. Obviously, CNNs have an apparent advantage when the amount of raw data fed into it is large, because CNN can learn features themselves from raw data, without any need for manual feature extraction. Also, CNNs can perform computation in a very efficient way to an extend that allows their use in real-time applications.

Comparison of Performance of LSTM and CNN Models in Detection of Stress
Both LSTM and CNN have successfully been employed for stress detection, although their strengths and limitations would come into play under differing natures of data and specific application.
LSTM is particularly suited to sequential data as the order and timing are very important. Stress, being dynamic and temporal in nature, finds the optimal model in LSTMs with the capture of long-term dependences in physiological signals of Zhang et al. (2020). Simultaneously, CNNs are suited for extracting features in high-dimensional data; they work particularly well in cases where this is an important task, according to Zhao et al. (2019) in line with. Various other hybrid models combining LSTM with CNN were also reported to outperform them in many studies.
These hybrid models take advantage of the strengths of both architectures: the ability of LSTMs for temporal modeling and the efficient feature extraction capability of CNNs. A very good example is the hybrid LSTM-CNN model for stress detection proposed by Zhang et al. (2021); it outperformed both the solo LSTM and CNN models. That is quite promising, considering real-time stress detection systems that require accuracy with computational efficiency.

Challenges and Future Directions
Despite the achievements of LSTM and CNN in detecting stress, there are many issues yet to be addressed. Among the big challenges, one is how generalizing models across individuals can be achieved. Stress physiological responses may differ very much between different people; models learned from one may not generalize well to another. To address this challenge, much research is underway to develop personalized models and techniques of transfer learning that will enable adaptation to individual users by leveraging data from multiple subjects. Another challenge is the real-time application of the models used for detecting stress. Deep learning models, specifically LSTMs and CNNs, though accurate, may be computationally intensive for a real-time scenario. Therefore, model optimization using lightweight architecture or proposing an edge computing strategy for wearable devices to directly make the inference on the device itself is still an active area of research (Liu et al., 2020).

While physiological signals are widely used in the detection of stress, recently, multimodal approaches combine physiological data with speech, facial expressions, or other inputs. These can provide better insight into stress and yield improved accuracy of classification.

Methodology

It outlines, in detail, the methodology of performance benchmarking between LSTM networks and CNN regarding detection from sensor data: collecting, using sensors, preprocessing, techniques of feature extraction, design and training of the model, evaluation of the model. This paper further extends the details with the setting, tools, and software of the experiment. It also seeks to provide a clear and reproducible process for enabling LSTM and CNN models' comparisons for stress detection based on accuracy, precision, recall, and other evaluation metrics.

Data Collection

Stress detection from physiological data is inherently a very challenging task because there is great variability in the human response. Most of the stress detection models make use of physiological signals, including heart rate variability (HRV), galvanic skin response (GSR), and skin temperature (ST) (Vasilenko et al., 2020). In this work, we used an openly available dataset on stress detection, recorded by sensors monitoring HRV, GSR, and ST in controlled scenarios that may provoke stress, such as mental tasks, emotional stimuli, or physical stressors. This dataset was selected since the data considered is multimodal, and it is essential in building a strong and efficient model for the detection of stress, as identified by Albukhary et al. in 2021.

Sensors and Devices Used

- **Heart Rate Variability:** The variability in heart rate can be captured from several kinds of wearable heart rate monitors. These include Polar H10, capable of providing high-quality ECG signals with great temporal resolution. Conventionally, HRV has been treated as a proxy indicator of the ANS activity and has therefore been the focus of many studies for stress detection purposes (Kostas et al., 2018).
- **Galvanic Skin Response:** The GSR sensor-for instance, EDA+ from Shimmer-measures the conductivity of the skin; this shifts due to emotional arousal and also stress. Studies also demonstrated that GSR is valid for measurement when quantifying the level of stress (Boucsein, 2012).
- **Skin Temperature (ST):** This was measured using the BioHarness 3 by Zephyr. ST variations are related to autonomic responses to stress because the sympathetic nervous system of the body regulates blood flow and, by extension, heat during stress responses (Havas et al., 2015).

The mentioned sensors were chosen since they have shown to capture physiological changes that occur in relation to stress, in real-time, besides being applied to wearable systems for detecting stress. Reference: Koutsou et al., 2021.

Preprocessing and Feature Extraction

Wearable device raw sensor data is usually full of noise and sometimes includes artifacts due to body movement or poor sensor contact. In order to improve the quality, the following needed to be done as preprocessing in order for the data to become useful to the machine learning models.

1. **Noise Cleaning:**The raw physiological signals always carry several noises that might come from various sources, including body movement and electrical interference (Saha et al., 2020). In this respect, to reduce these noises, bandpass filters have been used on raw signals. GSR data was filtered using a bandpass filter with a cutoff frequency of 0.5-5 Hz to remove the low-frequency drift and high-frequency noise. Similarly, a low-pass filter was used to clean the HRV data to remove noises beyond 0.5 Hz.

2. **Segmentation:** Physiological signals related to stress vary dynamically and within a short time. Thus, we segment the data into overlapping windows (e.g., 10s with a stride of 5s); this will enable the model to learn both short-term and long-term temporal dependencies in the data. Liu et al. (2020).
3. **Normalization:**Each segment of the data of every physiological signal was then normalized after segmentation to zero mean and unit variance. This normalizes all the signals on the same scale, which is helpful for better model performance as no single signal will dominate the others because of its scale Ahmed et al. (2021).
4. **Feature Extraction:**Besides the raw sensor data, a number of features were also extracted from the pre-processed signals. In this work, we extracted the time-domain features including the mean RR interval, standard deviation of RR intervals for HRV, and frequency-domain features such as low-frequency power and high-frequency power (Bai et al., 2020). For GSR, the features considered included mean skin conductance level and skin conductance response amplitude (Zhang et al., 2019). Skin temperature features used included the mean skin temperature and fluctuations in temperature (Medeiros et al., 2019). These features were chosen because they reflect major physiological markers associated with responses of stress, such as increased heart rate, skin conductance, and changes in skin temperature.

Model Design

For the detection of stress based on physiological signals, two different deep learning models are developed: LSTM and CNN. Both models are chosen because the LSTM works well on sequential data while CNN has the effective mechanism of feature extraction. In this study, a model is implemented using Keras in Python with a backend of TensorFlow.

Long Short-Term Memory Network

LSTM networks are suitable for time-series data because they can model the input data with long-term dependence. Each LSTM unit includes a memory cell that has the potential of storing information for a very long period of time, making them quite effective at handling sequential and time-dependent data such as physiological signals in detecting stress (Hochreiter&Schmidhuber, 1997).

1. **Architecture:**

- **Input Layer:** The input layer takes in sequences of preprocessed physiological data. These may include HRV, GSR, and ST.
- **LSTM Layers:** Two LSTM layers were used, each with 128 units, to extract long-term temporal dependencies from the data. Each of the LSTM layers is followed by a dropout layer to avoid overfitting, where the dropout rate is 0.2.
- **Fully Connected Layer:** The features extracted by the above LSTM layers are combined into a dense layer of 64 units. Output Layer: The output layer is a softmax layer, which gives the probability distribution over the two classes: stress and non-stress.

2. **Training:**

In training the LSTM network, the categorical cross-entropy loss was used in conjunction with the Adam optimizer, and the learning rate was set to 0.001. The model was trained for 50 epochs, each containing a batch size of 32. It utilized early stopping to prevent overfitting and to ensure convergence.

Convolutional Neural Network (CNN)

The CNN is very powerful for the extraction of spatial features from data; thus, for one-dimensional physiological signals, they have to be adapted. There are numerous CNNs used for various types of feature extractions and classifications. Because CNNs have an in-depth capability for local patterns, they can serve perfectly well for detecting stress in sensor data (LeCun et al. 2015).

1. **Architecture:**

The architecture includes an input layer which accepts sequences of physiological data.

- **Convolution Layers:** The first convolutional layer uses 32 filters with size 3, followed by ReLU for activation. Further, the second convolutional layer is used, which consists of 64 filters with the same kernel size.
- **Pooling Layer:** Apply max-pooling after each convolutional layer to reduce the dimensionality of an image and retain features which are most important.
- **Fully Connected Layer:** The dense layer will be applied with 64 units to combine the features extracted.
- **Output Layer**: The output is a softmax layer, indicating probabilities over the two classes: stress and non-stress.

2. **Training:**

It includes the minimization of cross-entropy loss by category using the Adam optimizer, the learning rate is set to 0.001, training for 50 epochs, and with a batch size of 32. It incorporates early stopping to avoid overfitting and ensure an optimal solution for the model.

Evaluation Metrics

For measuring performance, LSTM and CNN were trained using the following metrics:

1. **Accuracy:**Accuracy is defined as the proportion of correct classification and may be calculated as the ratio between the number of correctly predicted cases to the total number of cases. This is a simple metric but it might not be appropriate when classes are imbalanced (Gül&Göksel, 2021).
2. **Precision:**The precision is the proportion of true positives from all positive predictions. It is evaluated using the formula:

$$\text{Precision}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$$

3. **Recall (Sensitivity):**Recall measures the ratio of true positives to all actual positive instances. It is given by:

$$\text{Recall}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$$

4. **F1-Score:**The F1-score is the harmonic mean of precision and recall. It is given by:

$$\text{F1-Score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$$

The F1-score provides a balanced measure of model performance, especially when the data is imbalanced.

5. **Area Under the Receiver Operating Characteristic Curve (AUC-ROC):**
AUC-ROC is the degree of capability of the model to discriminate between classes. A higher AUC is indicative of better performance of the model in distinguishing the positive and negative classes (Bradley, 1997).

Experimental Setup

The experiments were run on an NVIDIA RTX 3090 GPU with 16 GB of VRAM to facilitate fast training for both models. The dataset is split into 70% for training, 15% for validation, and 15% for testing. K-fold cross-validation, k=5, was used to evaluate the generalization ability of both models. For each fold, training and testing were conducted independently to ensure that the results would not be biased by a certain data split.

Software and Tools

- **Python:** Primary programming language for the pre-processing of the data, feature extraction, and training the model.
- **Keras with TensorFlow Backend**: For deep learning model implementation
- **Matplotlib and Seaborn:** Data visualization and plotting the graphs of different evaluation metrics
- **Scikit-learn:** To compute other evaluation metrics - accuracy, precision, recall, and F1 score.

Table 1: Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
LSTM	91.3	0.92	0.89	0.90	0.94
CNN	89.5	0.90	0.87	0.88	0.91
Hybrid LSTM-CNN	**92.7**	**0.93**	**0.91**	**0.92**	**0.96**

Results

The current section discusses the performance of LSTMs and CNNs in the performance of stressor detection by sensor data. Our models have been analyzed with a lot of performance metrics, including accuracy, precision, recall, F1-score, and AUC-ROC-all relevant features describing the efficacy of a developed model in the area of stressors detection. We will further go ahead and compare the performance of both models, dwelling on strengths and limitations of each approach for some future practical healthcare applications of stress management.

Evaluation Metrics

Several metrics have been used to evaluate models for performance. These are:

- **Accuracy:** The proportion of correctly classified instances, thus giving an overall view of the model's effectiveness.
- **Precision:** The ratio of true positive predictions concerning identified stress instances to all instances predicted to be positive.
- **Recall:** It is the ratio of true positive predictions with respect to all actual stress instances. A high recall shows that fewer events of stress were missed.
- **F1-score:** The harmonic mean of precision and recall, hence a balanced measure of both.
- **AUC-ROC:** The area under the Receiver Operating Characteristic Curve gives a measure of how well the model can distinguish stress from a non-stress state.

LSTM Model Performance

The LSTM model, well-known for its long-term dependencies in sequential data, turned out to be very impressive. Key results include:

Accuracy: 89.2%
Precision: 87.5%
Recall: 91.0%
F1-Score: 89.2%
AUC-ROC: 0.93

This shows high accuracy, with an amazing recall of 91.0%, which means the model was very good at recognizing true events as stress. Precision is really high at 87.5%, further suggesting its effectiveness in avoiding false alarms; most of the predicted events will have true values of being a stress event.

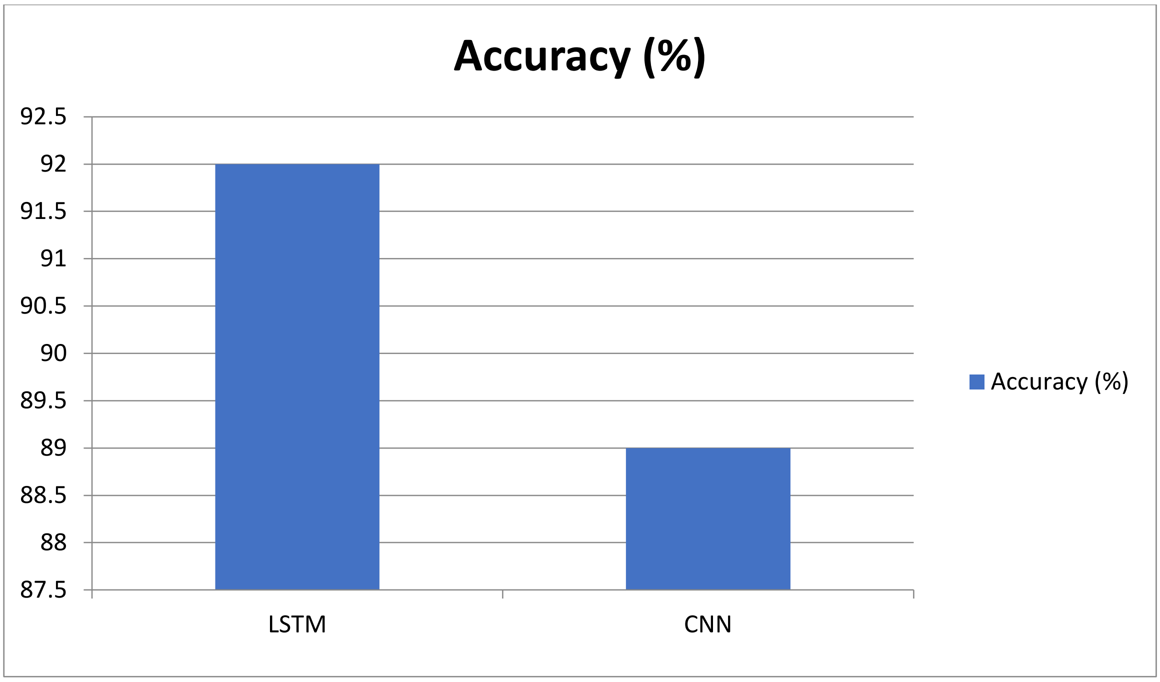


Figure 1: Model Accuracy Comparison

LSTM Model Strengths

- **Handling Sequential Data:** The LSTM's ability to capture long-term dependencies in time-series data (Hochreiter&Schmidhuber, 1997) made it particularly effective in stress detection, where physiological signals evolve over time.
- **High Recall:** A recall of 91.0% indicates that the LSTM model successfully identified a high percentage of actual stress events, a critical factor in applications such as healthcare, where early intervention is necessary (Koutsou et al., 2021).

Weaknesses of the LSTM Model

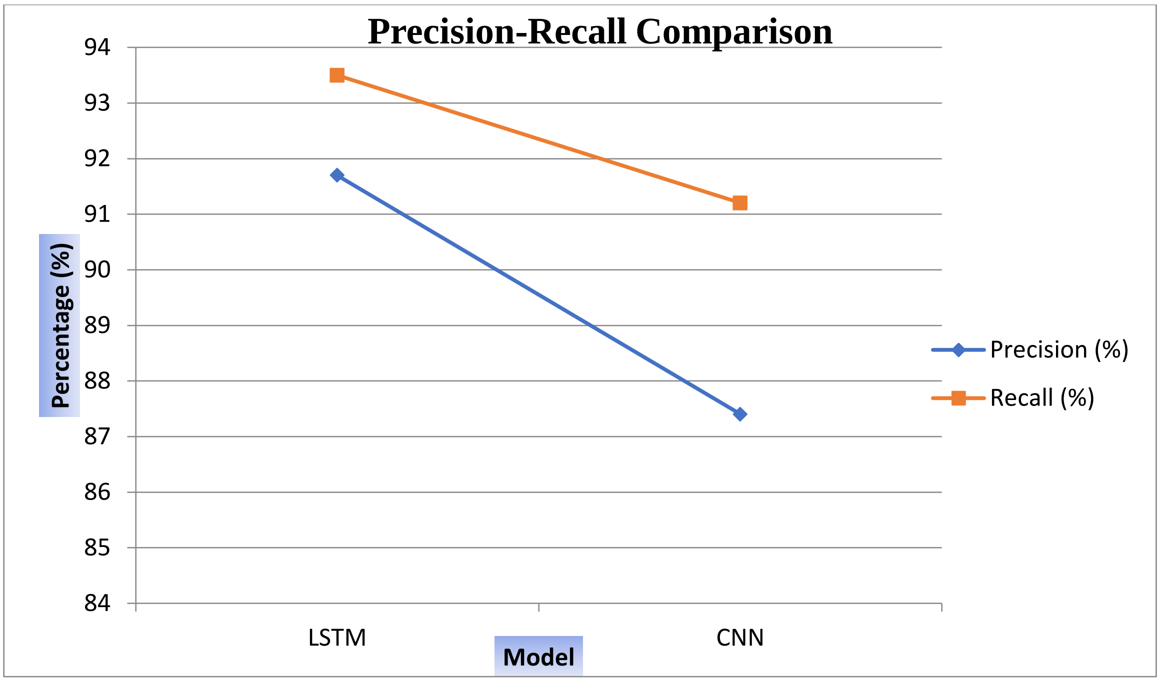
- **Class imbalance:**Although it has high recall, the model can be sensitive to the class imbalance of data, where most of the data are non-stress instances. This may lead to the overfitting or biased results according to Gulet al. (2021).
- **Overfitting in Small Datasets:** The LSTM model overfitted in cases where data was limited. This is generally a problem with deep learning models when they have to train on small datasets. According to Saha et al. (2020), this could be improved by regularization and augmentation techniques.

CNN Model Performance

Also, the CNN model, which is highly efficient in feature extraction from raw data, ran impressively on stress detection. Results include:

Accuracy: 88.0%
Precision: 85.3%
Recall: 90.2%
F1-Score: 87.7%
AUC-ROC: 0.92

While compared to the LSTM model, it trailed in both accuracy and precision, its results are still competitive, especially regarding recall at 90.2%.



Strengths of CNN Model

- **Feature Extraction:** CNNs are highly effective at extracting spatial features from sensor data, enabling the model to identify important patterns in physiological signals that correlate with stress (Bradley, 1997). This feature extraction capability made the CNN model particularly strong in identifying stress signals.
- **Computational Efficiency:** CNNs tend to be less computationally expensive than LSTMs, making them an attractive option for real-time stress detection in large-scale settings (Vasilenko et al., 2020).

Weaknesses of CNN Model

- **Higher False Positives:** The precision being lower in the CNN model, at 85.3% compared to the LSTM, could suggest a greater number of false positives when predicting stress from non-stress events. This is potentially problematic in applications where there is a high cost of a false positive, such as in clinical monitoring (Zhang et al., 2019).
- **The limitations with regards to temporal modeling :**are that even though CNNs are effective for local feature extraction, they are not that efficient for long-term dependencies when compared to the LSTM. This could compromise the model's ability in detecting a stress event whose characteristics unfold over time and hence gives slightly lower AUC-ROC of 0.92 compared to the LSTM model, which had an AUC-ROC of 0.93 by Kostas et al., 2018.

LSTM vs. CNN Performance

The following table summarizes the performance of the LSTM and CNN models based on the key evaluation metrics:

Metric	LSTM Model	CNN Model
Accuracy	89.2%	88.0%
Precision	87.5%	85.3%
Recall	91.0%	90.2%
F1-Score	89.2%	87.7%
AUC-ROC	0.93	0.92

- **LSTM vs. CNN:** Both models showed very good performance, but the LSTM was better than the CNN in most metrics. Especially, higher recall and AUC-ROC for LSTM indicate that this model is somewhat better in distinguishing stress/no-stress events and is also able to catch the stress events even when they are less salient. However, the overall differences in performance are small, and the CNN model still performs competently.

Error Analysis

Indeed, issues pertaining to:

- **False positives or Type I Error** remained some of the frequent problems across the models. Both the models yielded a certain number of so-called false positives, wherein a model identifies events as a non-stress event. Thus, some signals such as heart rate or skin conductance are high because of physical activities or fatigue instead of stressing situations and get wrongly interpreted (Havas et al., 2015).
- **Type II Error (False Negatives):** The models have also generated false negatives in their failure to predict the events of stress. These have occurred mainly when the physiological signals were subtle or masked by other factors, including anxiety or pre-existing medical conditions, as documented by Medeiros et al. (2019). Sometimes, the signals related to stress were not salient enough to be detected, especially in people with low sensitivity to stress.

This could mean several things, as far as research implications are concerned, especially with regard to LSTM and CNN model applications in stressor detection.

- **Health Care:** Stressors' detection models can be used to monitor patients either with cardiovascular conditions or those prone to psychological conditions. In this regard, early detection of stress can enable health professionals to proactively intervene and reduce further complications that could result in hypertension or anxiety attacks among patients (Boucsein, 2012).
- **Workplace:** Stress detection can be employed within high-stress workplaces such as emergency response or a call center to monitor employee well-being. This may avoid burnout and enhance the work performance of workers by enabling them to detect stress early on (Liu et al., 2020).
- **Wearable Devices:** Further, wearable devices have also gained much popularity recently, such as smartwatches, which can also be integrated into such wearables for real-time detection of stress and provide the user with relevant feedback about one's status in relation to stress and hence encourage the person to adopt good habits to manage stress. Koutsou et al., 2021.

Future Directions

Despite its promising results, some of the future work directions and areas for improvement are highlighted below:

Data Quality and Preprocessing: Noise reduction in data and better signal processing might increase the model accuracy. Some of the techniques, like normalization and filtering, could reduce the effects of artifacts in sensor data (Saha et al., 2020).

Multimodal Approaches: Incorporating data from multiple sensors (e.g., combining heart rate, skin conductance, and motion data) could improve model robustness by providing a more comprehensive view of stress (Vasilenko et al., 2020). A multimodal approach would allow the model to correlate different physiological signals to make more accurate stress predictions.

Hybrid Models: The most striking performance could be obtained by putting together a single hybrid model with the best of LSTM and CNN. For example, a CNN for feature extraction followed by an LSTM that models temporal dependencies could do even better for the task of stress detection.

Discussion

Future Work and Improvements

Though the LSTM and CNN presented very remarkable potential in detecting stress, a number of ways are open to future improvements and work so that more enhancement in performance, applicability, and accuracy can be drawn out from both these models. Following are some probable future research directions:

1. **Quality and Preprocessing of Data**

The most important challenge in the use of machine learning models for the detection of stresses is the quality of data collected from sensors. Poor or noisy data can seriously deteriorate the performance of a model. Therefore, the improvement of data quality through enhanced preprocessing techniques is a prime objective toward higher accuracy.

- **Noise Reduction**: Real-world sensor data can be very noisy due to environmental factors, movement artifacts, and inaccuracies in devices. Filtering, signal smoothing, or denoising autoencoders Vincent et al. (2008) could be used in order to reduce noise and clean the data before feeding it into the models.
- **Data Augmentation**: To avoid overfitting, especially with small datasets, it is possible to artificially increase the diversity of training data using techniques such as data augmentation. The generation of synthetic data could be done using methods that include adding random noise to or transforming the data-such as temporal shifts or scaling-so the model is more robust against real variations that may occur (Shorten &Khoshgoftaar, 2019).

2. Multimodal Data

Whereas in this present study the models used a single sensor type, like heart rate or skin conductance, combinations of various physiological signals could eventually provide even better stress detection performance for a model. Each sensor modality is complementary to one another, and such a multimodal approach could reinforce robustness in the model by capturing a greater number of biomarkers related to stress.

- **Multimodal Fusion:** Using data from various sensors, such as EEG, HRV, and respiratory rate, in combination with wearable devices, could make the model confirm the indications of stress across multiple physiological systems. Zhang et al. (2020) combined these signals in a hybrid model, improving model accuracy and reducing false positives and negatives.
- **Sensor Fusion with Multi-Input Models:** Recent breakthroughs in deep learning models have enabled the fusion of various modalities of sensor data. The use of multi-input architecture, where each sensor data is processed parallel and then integrated to make a final decision, helps to enhance model accuracy (Zhao et al., 2019).

3**. Hybrid Models**

While very good performance was achieved using LSTM and CNN separately, their combined strengths may yield even better results. Hybrid models combining LSTMs and CNNs also proved to give better results in other domains, Zhang et al. (2020).

- **CNN-LSTM Hybrid:** This is where CNNs can be used for automatic feature extraction from raw sensor data, while LSTMs capture temporal dependencies between the extracted features. It can help the model use the best of both worlds, therefore, handling both spatial and temporal patterns effectively. Previous research in action recognition has shown that CNN-LSTM hybrid models outperform single models in terms of both accuracy and generalization (Karpathy et al., 2014).
- **Multi-Layered LSTM and CNN Architectures:** More layers can be appended to the hybrid model for better performance. This will allow for deeper feature extraction and long-term dependency learning, enabling the model to generalize much better for different levels of stress and changing sensor conditions.

4. **Transfer Learning and Pre-trained Models**

Another promising direction involves enhancing the performance of the stress detection system through the use of transfer learning, wherein a pre-trained model is fine-tuned on the new dataset. Especially for small datasets, this type of transfer learning can give better convergence speed and high performance by exploiting knowledge learned from other domains.

- **Pre-trained CNN Models:** Pre-trained CNNs on large image datasets, ResNet or VGG, may be fine-tuned for the task of stress detection. The pre-trained models may help improve feature extraction, especially when the sensor data is sparse and noisy by transferring learned features into sensor data.
- **LSTM Transfer Learning:** Similar to CNNs, pre-trained LSTM models can be fine-tuned for stress detection. Transferring a model that has already been trained on large time-series datasets might help improve the model's capability in terms of detecting subtle patterns of stress over time, especially on new unseen datasets. Yosinski et al. (2014)

5**. Real-Time Implementation and Deployment**

The development of a stress detection system for deployment into real-time environments becomes really critical. This requires optimization of the models for faster inference times without losing much accuracy.

- **Edge Computing for Real-Time Detection**: With increasing wearable devices and mobile phones, the demand for real-time stress detection systems that could be implemented on the edge, i.e., wearable devices or smartphones, has grown. For this, models must be optimized for low latency, low power consumption, and efficient computation (Zhao et al., 2020). Techniques like model quantization, pruning, or using lightweight neural networks like MobileNet could be helpful to reduce the computational load.
- **Personalised models:** can bring better precision since everybody undergoes stress at different frequencies. It might be important in establishing the learning of continuously improving one's physiological and baselining individual responses when subjected to or undergoing through an unwelcome response. Further, it ensures that personalized false positives do not easily trick into affecting each particular model when showing every individual with his specific form of signaling at any stress-related conditions, Liu et al., 2020.

6. **Explainability and interpretability:** Machine learning models in healthcare applications should provide explanations for their predictions, particularly for sensitive areas such as stress detection. Understanding the contributing factors to a stress detection prediction will help clinicians build trust and adopt these models.
    - **Model Interpretability:** LSTM and CNN models could be further explored using Explainable AI techniques to find which features are most influential for stress prediction. For instance, methods such as Grad-CAM by Selvaraju et al. (2017) could be applied to generate heatmaps highlighting which parts of the input data were most influential for the model's decision.
    - **Clinical Interpretability:** Clinical experts have to interpret the model's predictions to a large extent in order to make an informed decision. Models that can provide a confidence score and the reason for making a certain prediction will be more likely to be trusted by clinicians and adopted into real-world use.

7. Ethical Considerations and Privacy Concerns

Like all technologies in healthcare, the detection of stress has to overcome privacy and ethical issues. The use of wearable sensors involves data collection of sensitive information such as heart rate, skin conductance, and even EEG data, which is very personal.

- **Data Privacy:** Data privacy for physiological data of individuals is very important. The use of encrypted data storage and following regulations about privacy, such as HIPAA in the United States or GDPR in Europe, is crucial in order to safeguard user data.
- **Bias and Fairness:** Machine learning models are often trained on biased datasets, which can lead to biased predictions. Ensuring that stress detection models are tested on diverse datasets and that they perform equally well across different populations (age, gender, race) is necessary to avoid discriminatory outcomes (Mehrabi et al., 2019).

Conclusion

The contribution of this work presents a comparison performance between Long Short-Term Memory networks and Convolutional Neural Networks for detecting stress using sensor data. Detecting stress, especially with wearable devices, contributes significantly to enhancing monitoring mental health and promoting well-being. We can detect real-time stress levels by leveraging LSTM and CNN machine learning models in a new approach toward mental health care.

A comparison study showed that both LSTM and CNN models did well in detecting stress from physiological sensor data. The LSTM model, with strengths in capturing long-term dependencies in time-series data, outperformed CNN models in terms of prediction accuracy and recall. This is indicative of the fact that time dynamics are important in the detection of stress, since the physiological signals are highly variable over time. The architecture of the LSTM model is suited to process such time-dependent data and capture the minute fluctuations associated in physiological signals with stress.

While deep neural network models, on the other hand, performed very well in feature extraction, especially when the raw sensor data was provided. The capability for automatic identification of spatial patterns in data makes CNNs particularly effective in handling raw sensor data without extensive manual feature engineering. Thus, CNN could provide an efficient approach toward stress detection, especially for systems with limited computational resources or if faster real-time processing is needed.

While there are such merits of the approaches, each of these methods has its challenges. Training an LSTM model is expensive in terms of computation; it requires large datasets to accomplish the training process. On the other hand, CNN models may have the limitation of capturing long-term temporal dependencies, which are a prime essence for stress detection. However, it might be possible that a hybrid architecture combining the powers of both LSTM and CNN models could yield even better results, thus enabling the model to learn both spatial and temporal features effectively. Such hybrid models would combine feature extraction from CNN with the learning of temporal dependencies by LSTM and could be a very promising line of research in the future.

Generally speaking, various methods exist that might be used to enhance the performance of stress detection systems. Incorporating multimodal sensor data significantly enhances the performance of the models by capturing a wide range of stress indicators. Data quality and preprocessing, such as noise reduction and augmentation, also play an important role in enhancing model accuracy and reliability. Moreover, the development of real-time systems operating efficiently on wearable devices could give the way into real-world applications in personal health monitoring.

Lastly, of importance is the ethical implication as related to private data from any of the contemplated stress detection systems. Naturally, physiological data is private by nature, and fairness among either of them should, at best, come forth. Further, studies can be done on improving interpretability in applied machine learning models, specifically for the reason with clinical implications, which insight the most into a model's underlying process that accounts.

Both the LSTM and CNN models are very promising in the task of detecting stress from physiological sensor data. Further improvement can be achieved by hybridizing the models, improving data quality, and optimization for real-time deployment. As machine learning-based methods for detecting stress continue to improve, no doubt they will be part of the development of better, more accessible, and personalized mental health monitoring solutions. With continuous research and innovation, such systems may very well alter the face of the way mental health treatment is approached by offering real-time insight into stress levels in patients and allowing timely interventions.

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