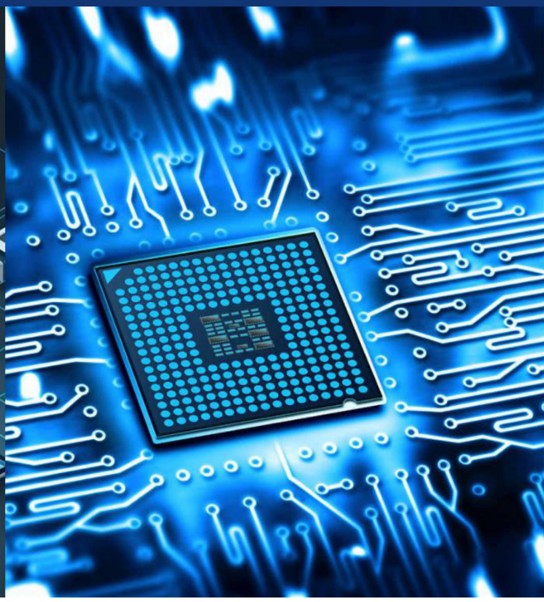
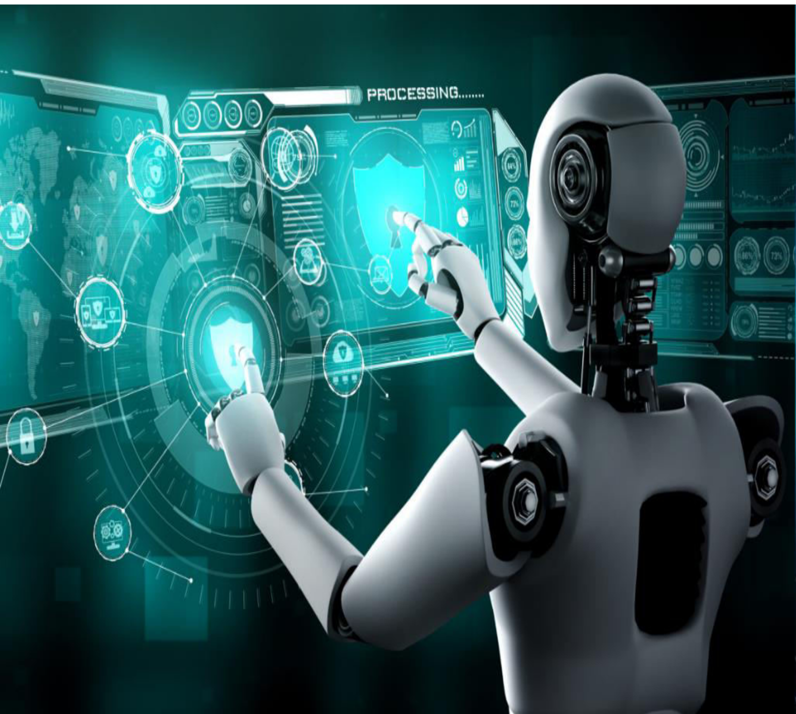
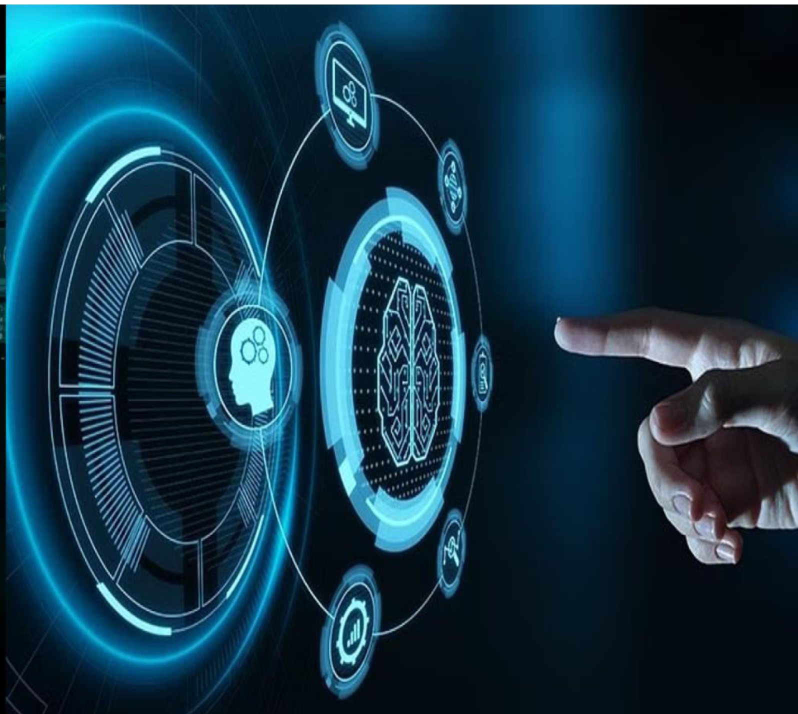
ISSN(O): 2320-9801
ISSN(P): 2320-9798


International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 13, Issue 4, April 2025

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304096

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Fear Detection Using Physiological Signals with LSTM-SVM Hybrid Framework for Enhanced Safety Applications

M.Narayanan[1], Paparaju Sai Varshini[2], Myakala Shirisha[3], Maramganti Sai Chetan Reddy[4], Mohammad Abdul Abu Sofian [5]

Professor, Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, Telangana, India[1]

UG Scholar, Department of CSE, School of Engineering, Malla Reddy University, Hyderabad, Telangana, India[2345]

ABSTRACT: Emotions play a critical role in understanding human behavior, with fear being one of the most essential and complex emotions to detect. Fear is a fundamental emotion that influences human behavior and decision-making. Detecting fear using physiological signals can significantly improve safety applications, such as security surveillance, mental health monitoring, and emergency response systems. This project focuses on fear detection using physiological signals such as heart rate, HRV, Respiration Rate, etc. The existing systems for fear recognition often rely on unimodal data, such as facial expressions, speech signals, or text, which lack accurate detection in real-time implementation, making them less suitable for practical safety applications. This study proposes an LSTM-SVM hybrid framework using Python to classify fear from physiological signals effectively. LSTM captures temporal dependencies in the data, while SVM enhances classification accuracy. The proposed model is trained and evaluated using a physiological dataset, demonstrating improved performance compared to conventional approaches. This enhances the system's ability to classify fear with greater accuracy. Applications in the safety of women, children, or elders, as such systems could alert authorities or trusted contacts in real-time during threatening situations.

KEYWORDS: Fear Detection, Machine Learning, LSTM, SVM, Python, Hybrid Framework, Classification, Physiological Signs, Heart Rate, HRV, Respiration Rate.

I. INTRODUCTION

Fear is a natural emotional response to perceived threats or danger, triggering physiological changes in the human body. It plays a critical role in survival by activating the "fight-or-flight" response, which prepares the body to react to potential dangers [7]. One of the most noticeable physiological changes during fear is an increase in heart rate and variations in blood pressure, respiration rate, and HRV. These physiological signals serve as measurable indicators of emotional states and have been widely studied in psychology, neuroscience, and biomedical engineering [5]. In recent years, advances in artificial intelligence (AI) and machine learning (ML) have made it possible to analyze physiological signals, such as heart rate data, to detect emotional states, including fear [9]. The ability to accurately identify fear using heart rate variations has significant implications across multiple domains, including mental health monitoring, security systems, virtual reality experiences, and human-computer interaction [3]. Existing emotion recognition methods rely on self-reported emotions or facial expression analysis, which can be subjective or influenced by external factors. However, physiological signals provide a more objective and reliable means of assessing emotional states. This research focuses on fear detection using heart rate, HRV, and Respiratory Rate data and employs two powerful machine learning techniques: Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) networks. SVM is a robust supervised learning algorithm known for its ability to classify data efficiently by finding an optimal decision boundary. It is widely used in various classification problems, including emotion recognition. In this study, SVM is applied to distinguish between normal heart rate patterns and those associated with fear responses. On the other hand, LSTM, a specialized form of Recurrent Neural Networks (RNNs), is well-suited for analyzing sequential data, making it highly effective for time-series analysis of heart rate fluctuations. Since heart rate variations occur over time, LSTM models can capture long-term dependencies in the data and improve fear detection accuracy [10].

The methodology for this study involves collecting the data from individuals exposed to different stimuli designed to induce fear. This data is then preprocessed to remove noise and extract relevant features. The extracted features are used to train both the SVM and LSTM models. The performance of these models is evaluated using accuracy, precision, recall, and F1-score metrics to determine their effectiveness in fear detection. Additionally, comparisons are made between the two approaches to assess their strengths and limitations. One of the key challenges in fear detection using heart rate data is ensuring the accuracy and reliability of the system in real-world scenarios. Heart rate fluctuations can be influenced by various factors such as physical activity, stress, and environmental conditions. Therefore, it is essential to develop robust machine-learning models capable of differentiating fear-induced heart rate changes from other physiological variations. Feature engineering techniques, such as heart rate variability (HRV) analysis, frequency domain features, and statistical measures, play a crucial role in improving the model's performance.

The applications of fear detection systems based on heart rate analysis are extensive. In healthcare, such systems can be used to monitor patients with anxiety disorders, phobias, or post-traumatic stress disorder (PTSD). By detecting fear-related physiological responses, healthcare professionals can provide better interventions and treatment plans. In the field of security, fear detection can be used in lie detection systems, behavioral analysis, and threat assessment in high-risk environments [11]. Virtual reality (VR) applications also benefit from fear detection by adjusting immersive experiences in real time based on the user's emotional state.

Besides, human-computer interaction (HCI) can be improved through the incorporation of face detection in smart systems that react to the emotions of users in real time. The effectiveness of this fear detection system has many practical uses in many fields. In medicine, it can be used to monitor patients with phobias, post-traumatic stress disorder (PTSD), and anxiety disorders, enabling clinicians to quantify emotional states and intervene in a timely fashion. In security and law enforcement, fear detection can be used for lie detection, threat assessment, and behavioral surveillance, complementing surveillance and forensic interrogation. The entertainment and virtual reality sectors can utilize the technology by creating emotion-adaptive experiences, such as video games or simulation environments reacting in real time to the degree of fear. Moreover, human-computer interaction and artificial intelligence systems can utilize the face detection capability to develop more responsive and sensitive interfaces that adapt to users' emotional states.

With the advancement of artificial intelligence and machine learning, detection of fear from heart rate signals is a significant breakthrough towards the development of emotion-aware technologies. The combination of biomedical signal processing, deep learning, and physiological analysis in this research is a testament to the future potential of affect recognition systems on the basis of AI to transform various industries. The data-driven, objective detection of fear in this research is supplemented by the rapidly emerging area of affective computing, in which machines are designed to identify, understand, and respond to human emotions effectively [13]. The results and findings in this research can serve as a foundation for additional research on enhancing mental health monitoring, biometric security systems, and immersive user experiences. The remainder of this report contains an extensive explanation of methodology, implementation, data analysis, and experimental results that provide insights into the real-world consequences and challenges of fear detection by SVM and LSTM-based models.

II. LITERATURE SURVEY

Emotion recognition has advanced significantly over the years, with researchers exploring various methods to enhance accuracy. External signals such as facial expressions, body gestures, and speech have traditionally been popular due to their ease of collection using common devices like smartphones and computers. Schuller (2018) [5] and Byoung (2018) [5] demonstrated how deep learning could improve the recognition rates for such external signals. These methods, however, face certain challenges. Privacy concerns, device dependency, and limited reliability in uncontrolled environments hinder their practical applications. Consequently, researchers have shifted focus to internal physiological signals, including EEG, GSR, and heart rate data. Shu et al. (2018) [1] emphasized that these signals are more reliable but require expensive equipment and controlled environments for effective analysis. Despite these challenges, wearable technologies like EEG-integrated headbands are broadening the accessibility of physiological signal-based emotion recognition [4]. These advancements are crucial for applications that demand high accuracy in real-time scenarios. Fear detection, as a subdomain of emotion recognition, holds immense significance in areas like healthcare, therapy, and safety. Studies in this field have primarily relied on physiological signals to detect fear responses. Liu et al. (2009) [6] investigated fear detection using EKG, GSR, and EMG data during gaming sessions. They achieved an accuracy of 88% using a Regression Tree model, showcasing the potential of these signals. However, their method was limited by the need for multiple sensors and lacked scalability. Similarly, Bălan et al. (2020) [7] explored fear detection in individuals with acrophobia using a virtual reality game and KNN classifiers. Their system achieved only 52.75% accuracy, reflecting the limitations of simpler machine learning models. Gutierrez-Martín et al. (2022) [13] compared physiological signals with catecholamine concentration for fear detection, revealing critical insights into the effectiveness of different methods. While these studies highlight the growing interest in fear detection, they underscore the need for better approaches that integrate advanced algorithms to improve accuracy and scalability.

Deep learning methods have significantly impacted the field of emotion recognition. Hu et al. (2018) [10] demonstrated this by employing deep Convolutional Neural Networks (CNNs) and EEG spectral images to detect fear of heights, achieving an accuracy of 88.77%. This study highlighted the efficiency of deep learning in capturing intricate patterns in physiological data. Meanwhile, Picard and Healey (1997) [4] introduced effective wearables that combined EEG and GSR data for emotion classification. Though innovative, such multimodal systems are expensive and challenging to implement in real-world scenarios. The dependency on high-end equipment and the complexity of feature extraction remain significant hurdles. Kanjo et al. (2019) [15] further explored mobile-based deep learning approaches for emotion recognition, proving their feasibility for real-world applications. These advancements indicate the potential of deep learning while emphasizing the need for cost-effective and simpler alternatives.

Despite significant progress, many existing systems face challenges in real-world environments. Unimodal approaches relying on speech or facial recognition fail to capture the complexities of emotions like fear. Systems based on EEG or peripheral sensors, though accurate, require significant computational resources and expertise for feature extraction. Appelhans and Luecken (2006) [3] highlighted the utility of heart rate variability (HRV) as a simpler yet effective measure for emotional responses. However, HRV-based systems often lack integration with advanced classifiers capable of real-time processing. Schmidt et al. (2018) [9] introduced the WESAD dataset, which provides multimodal physiological signals for affective computing research, aiding in the development of real-time emotion detection models. This gap presents an opportunity for hybrid systems that combine the strengths of physiological signals and machine learning models to overcome these limitations. Improving scalability and real-time responsiveness is essential for practical applications in fields like healthcare and safety.

The proposed system integrates heart rate data with advanced machine learning classifiers to detect fear. By combining Long Short-Term Memory (LSTM) networks and Support Vector Machines (SVM), the system leverages the strengths of both methods. LSTM networks excel at processing sequential data, making them ideal for heart rate signal analysis. On the other hand, SVM offers robust classification capabilities, especially in small datasets. Schäfer et al. (2018) [9] emphasized the importance of HRV biofeedback in fear-inducing situations, making HRV a valuable feature of this system. Awais et al. (2021) [10] highlighted the effectiveness of LSTM-based emotion detection models in real-world applications, further validating the approach. Unlike previous models, the proposed system eliminates the need for manual feature extraction, offering faster and more reliable results. This approach ensures scalability and real-time applicability, making it suitable for critical applications in healthcare and safety.

The focus of this research is to develop a robust, scalable system that can accurately detect fear in real time. Heart rate data, easily captured using wearable devices, ensures practicality and accessibility. By integrating LSTM and SVM, the system addresses the shortcomings of existing solutions, such as high complexity and limited real-time capabilities. Miranda et al. (2019) [12] proposed an affect recognition model for fear detection, demonstrating its effectiveness with limited physiological signals. Additionally, Miranda et al. (2021) [11] explored a reduced set of physiological signals for fear recognition, aligning with the objectives of this work. In the future, the project will use multimodal data, such as combining HRV with GSR or EEG for enhanced accuracy. Ohman (2005) [6] further emphasized the role of the amygdala in human fear responses, reinforcing the scientific basis of this approach. This work aims to set a benchmark for emotion recognition technologies by bridging the gap between research and practical implementation, significantly benefiting healthcare, safety, and related domains.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

III. PROPOSED SYSTEM

The proposed system enhances fear detection accuracy and real-time adaptability using a hybrid LSTM-SVM system. The advantages of both models are leveraged in the system: LSTM detects temporal patterns in heart rate, HRV, and respiratory rate, and SVM delivers robust classification performance. By leveraging the synergy of deep learning and traditional machine learning, the system minimizes the need for manual feature extraction and improves adaptability across different subjects. The method is to acquire physiological data from subjects exposed to fear-inducing stimuli. The data is preprocessed to remove noise, and the problem-specific features are extracted before training the SVM and the LSTM models. Effectiveness is measured in terms of performance metrics such as accuracy, precision, recall, and F1-score. Compared to the two methods, the new system achieves optimal fear detection in real-world applications.

One of the most important applications is mental health monitoring, where it can assist in the detection of anxiety disorders and PTSD, security systems, where it enhances lie detection and threat assessment, and virtual reality experiences, where it can dynamically manage immersive scenes. Human-computer interaction (HCI) can also be enhanced with fear detection by enabling AI-based systems to dynamically react to users' emotions. By combining biomedical signal processing, deep learning, and physiological analysis, the system presented in this work is anticipated to establish an improved, real-time, and more precise model for fear detection that can lead to the development of affective computing and emotion-aware technology.

3.1 Algorithms Used LSTM (Long Short-Term Memory)

This Project used a hybrid framework using LSTM and SVM algorithms. Let us know how each of the algorithms are used in the project for fear detection:

LSTM is a type of recurrent neural network (RNN) for sequence data. It is particularly suitable for time-series applications, such as handling physiological signals (e.g., heart rate, HRV, etc) in this project. LSTM is a distinctive form of Recurrent Neural Network that can handle the problem of vanishing gradients that plague RNN. LSTMs are designed specifically to circumvent the issue of long-term dependencies. LSTM architectures incorporate the memory cell, which is managed by three gates: the input gate, the forget gate, and the output gate.

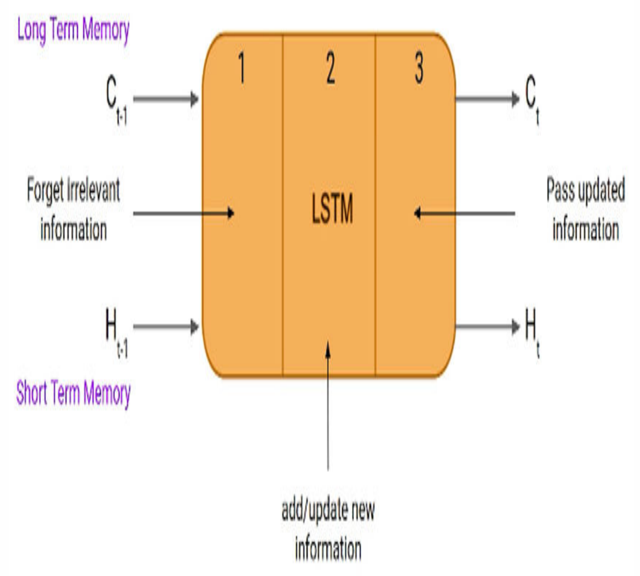


Fig.3.1: LSTM Architecture

Forget Gate: The forget gate decides which information from previous time steps is no longer useful and should be removed.

What Data is Forgotten? In fear detection, the LSTM forgets the random fluctuations in heart rate or respiration rate that are not linked to fear (e.g., due to physical movement or other emotions). The Short-term spikes that are inconsistent over time could be considered noise. Old patterns that no longer contribute to the fear prediction at the current moment. Forgetting ensures that the model does not hold on to unnecessary or misleading data, allowing it to focus on real fear-related patterns.

Input Gate: The input gate decides how much of the current physiological data should be added to the memory.
What Data is Stored? The Recent heart rate and respiration rate values, which indicate whether fear is present. Changes in physiological signals (e.g., a continuous increase in heart rate might signal fear). New trends that help detect fear, such as a decreasing heart rate after a fear response. The input gate ensures that only relevant new information is stored while preventing unnecessary data from overwhelming the memory.

3.2 Short Term Memory (Hidden State):

Short-term memory (hidden state) carries the most recent and relevant data for immediate decision-making. It contains the current physiological values (heart rate, respiration rate, variation), recent fear-related changes in heart rate or respiration rate. The most useful short-term information that helps in detecting immediate fear reactions. The hidden state is used for real-time prediction and is passed to the next LSTM unit to help make future decisions.

3.3 Long-Term Memory (Cell State):

Long-term memory (cell state) stores important patterns and trends that the model has learned over time. It contains the historical patterns of heart rate and respiration rate that indicate fear responses and the consistent trends in physiological data that help distinguish fear from normal fluctuations. Important fear-related signals from past observations, helping the model detect fear more accurately in future situations. Long-term memory allows the model to recognize deeper patterns rather than reacting to momentary changes.

Output Gate: The output gate determines what part of the memory should be used to generate the final prediction. The processed information is about whether fear is detected or not. The refined short-term memory, which will help in predicting the next time step. Only the most useful features of heart rate and respiration rate, after filtering out unnecessary data. The output gate ensures that only the most relevant and meaningful processed data is used for the final fear classification.

These are the steps that are carried out by LSTM in this project are Preprocessing, LSTM Model Structure, Dropout and Batch Normalization, and Feature Extraction. In Preprocessing, the physiological input data is reshaped to the target LSTM input shape, which is usually (samples, time steps, and features). Then, in the next step, LSTM Model Structure, the code specifies an LSTM network with two layers. In Dropout and Batch Normalization, these layers are probably included to avoid overfitting and enhance model stability. The last step is Feature Extraction, where the LSTM model learns temporal patterns from physiological signals and encodes significant features of fear.

3.4 Support Vector Machine

After feature extraction by the LSTM model, these are used as input to an SVM classifier for making the prediction. The output of the LSTM is a reduced feature vector that captures the temporal dynamics of the input signals. SVM (with sklearn.svm.SVC) is trained on the above features to classify if a given physiological response maps to fear or not. The model could apply GridSearchCV to optimize hyperparameters (i.e., type of kernel, value of C) for higher accuracy.

3.5 Hybrid Framework (LSTM+SVM)

LSTM excels at extracting meaningful sequential patterns from time-series physiological signals. SVM is a strong classifier for high-dimensional feature spaces and works well for binary classification problems like fear detection. Combining LSTM (feature extraction) with SVM (classification) improves accuracy over using either model alone.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304096

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

3.6 Overall Architecture

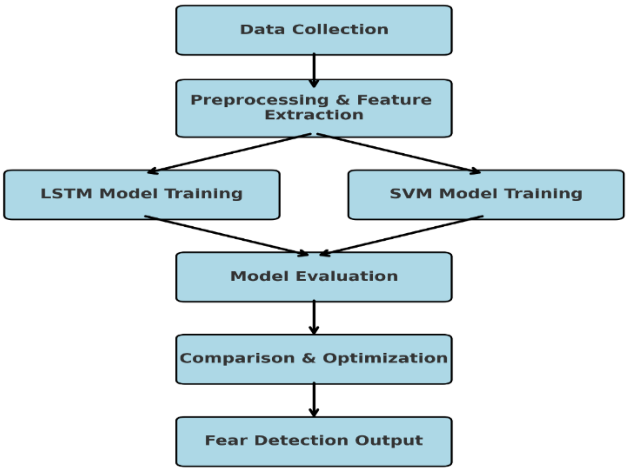


Fig 3.2: Overall Architecture

Fig.3.2 is the overall architecture of the fear detection system, and it begins with the data collection, where physiological signals like heart rate, heart rate variability (HRV), and respiration rate are collected to detect fear in this project. As the data contains noise due to external factors, the preprocessing and feature extraction stage plays an important role where the noise is removed and useful features are extracted instead of all the unnecessary features. After this step, the data is used to train two machine learning models: LSTM and SVM. The LSTM is trained to recognize the pattern in the data. Simultaneously the SVM model is also trained to detect the fear from the extracted features. After training the models, the model is evaluated using accuracy, precision, recall, and F1-score to determine their effectiveness.

Then comparison and optimization stage identifies the strengths and weaknesses of each approach, leading to further refinements in the hybrid model. The last step is the fear detection output, which determines whether an individual is experiencing fear or not.

3.7 Use Case Diagram

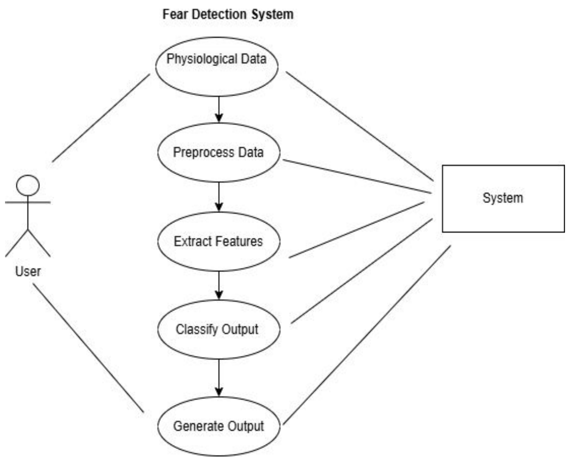


Fig.3.3: Use case Diagram

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Fig.3.3 is the Use Case Diagram that graphically depicts the interaction between users and the system, showing the primary processes involved in detecting fear from physiological data. The diagram has a systematic flow where users input physiological data, which are processed step by step to identify if fear exists. The participation of the system in various phases, including preprocessing, feature extraction, classification, and generation of output, guarantees systematic fear detection.

The initial step in the diagram is users sending physiological information, including heart rate, heart rate variation, and respiration rate. The information is preprocessed to eliminate noise and inconsistencies to ensure that only meaningful and high-quality input is applied for feature extraction. The preprocessing of features is very important for enhancing the accuracy of the classification process. The features extracted are the basis upon which the fear patterns in the physiological signals are recognized, and through that, the system is able to make informed decisions.

During classification, the features that have been extracted are checked with machine learning models like LSTMs or SVMs to identify whether there is fear or not. The system categorizes the data into "fear" or "no fear" labels according to the patterns learned. The output is then generated and returned to the user or other applications connected for further utilization. This organized flow guarantees a consistent and accurate process of fear detection, which makes it applicable to different applications such as psychological research, security systems, and health monitoring.

3.8 Class Diagram

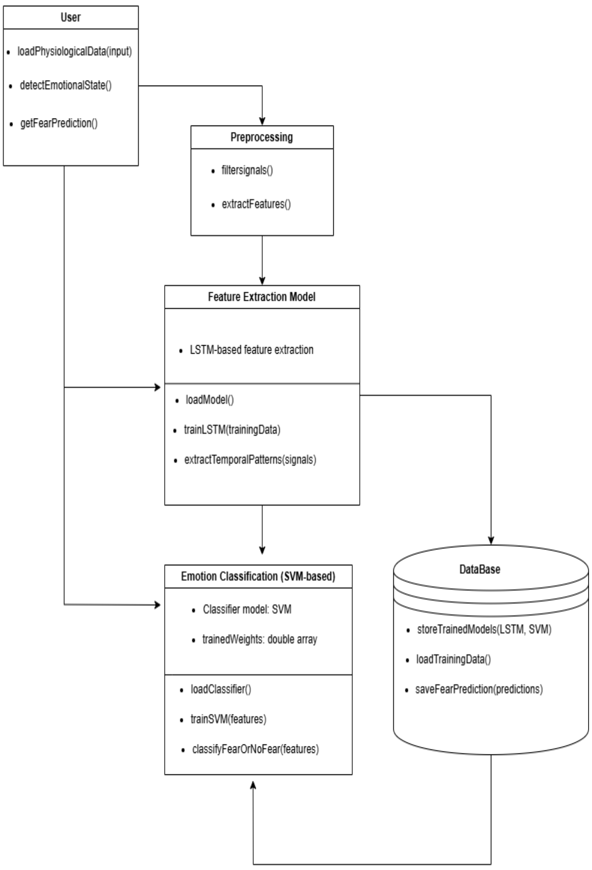


Fig.3.4: Class Diagram

Fig.3.4 is the Class Diagram based on physiological signals for emotion classification using LSTM and SVM models. It illustrates various classes involved in the system, such as User, Preprocessing, Feature Extraction Model, Emotion Classification, and Database. The diagram accurately identifies the major functionalities of each entity and their interaction, providing a systematic and modular solution to fear detection. It emphasizes how user inputs (e.g., heart rate, respiration rate, etc.) are processed using LSTMs to extract features and then classified using SVMs to predict the presence or absence of fear.

The User class will interact with the Preprocessing class, where raw physiological data is processed with signal filtering and feature extraction. These preprocessed signals are then sent to the Feature Extraction Model, which makes use of LSTMs to examine temporal patterns in the physiological data. The feature extraction model has pivotal methods like loadModel(), trainLSTM(training data), and extractTemporalPatterns(signals) to ensure that important features are extracted prior to classification. These extracted features are then sent to the Emotion Classification (SVM-based) class, where an SVM model is employed to classify the emotions according to trained weights.

Database class is essential to store and fetch critical data like trained models, training data, and predictions. It helps save fear predictions by the system so that they are available for future analysis or live monitoring. Data flow between database, feature extraction model, and classification module provides a smooth exchange of data, making the system scalable and fault-tolerant. This organized methodology improves the robustness of the Fear Detection System, rendering it appropriate for real-time applications in mental health tracking, security, and affective computing.

3.9 Sequence Diagram

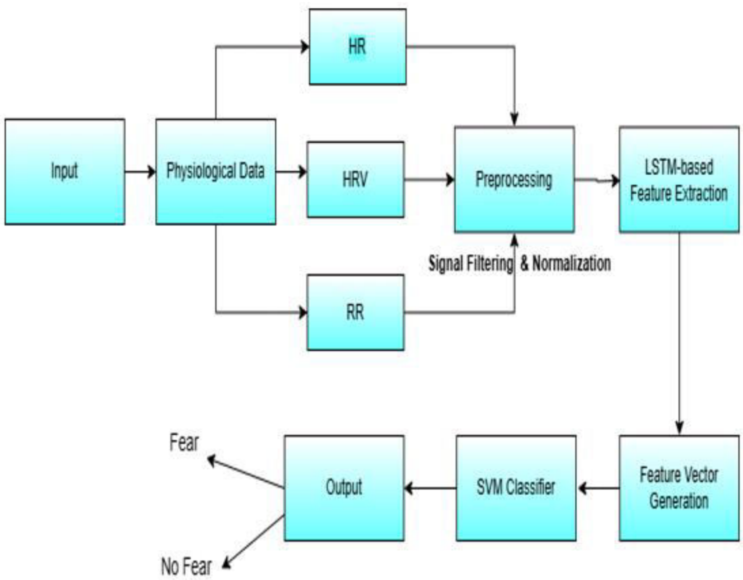


Fig.3.5: Sequence Diagram

Fig. 3.5 shows how input data, which includes physiological signals like Heart Rate (HR), Heart Rate Variability (HRV), and Respiration Rate (RR), is processed through several stages to label emotional states as Fear or No Fear. The process starts with the acquisition of physiological data, followed by preprocessing using signal filtering and normalization methods to eliminate noise and provide data consistency. This preprocessing process is essential to enhance the quality of the extracted features so they are more robust for subsequent machine-learning applications.

After preprocessing, the preprocessed physiological signals are fed into the LSTM-based feature extraction module. LSTMs are most appropriate for this purpose because they can learn temporal relationships in consecutive physiological data, enabling the system to identify minute changes in heart rate and respiratory patterns over time. After the LSTM model learns significant features, a feature vector is formed, which is passed on as input to the SVM classifier. The final classification decision is made by the SVM classifier based on the learned features. SVMs perform well with high-dimensional feature spaces and are heavily used for binary classification tasks, e.g., discriminating fear from no-fear states.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

The last stage in the pipeline is the classification output, where the system computes whether the subject is fearful or not. The prediction of the SVM classifier is passed to the output module, which gives a clear indicator: Fear or No Fear. The systematic process guarantees accurate and efficient emotion detection and is therefore beneficial for usage in mental health surveillance, security monitoring, and affective computing. The union of LSTM temporal feature extraction and SVM classification provides this system with strength and ability to deal with intricate physiological patterns related to emotional responses.

IV. RESULTS AND DISCUSSIONS

The database used in the project has 5,000 samples and the three physiological parameters—Heart Rate (bpm), Heart Rate Variability (HRV), and Respiratory Rate (breaths/min)—are measured on two states: exercise and fear.

FEATURE	DESCRIPTION	DATA TYPE
Heart Rate (bpm)	Number of heartbeats per minute	Integer
HRV (ms)	HeartRate Variability in milliseconds	Integer
Respiratory Rate (breaths/min)	Number of breaths per minute	Integer
Label	The physiological condition: "0 (Exercise)" or "1 (Fear)"	Categorical

Table 1: Databse

Table 1 shows that there is a single row for every physiological measurement recorded from a subject in the exercise or fear condition. The data set seeks to distinguish between fear response and exercise-induced changes in the physiological signals using machine learning classifiers.

The implementation begins with the data collection, where physiological signals like heart rate, heart rate variability (HRV), and respiration rate are collected to detect fear in this project. As the data contains noise due to external factors, the preprocessing and feature extraction stage plays an important role where the noise is removed and useful features are extracted instead of all the unnecessary features. After this step, the data is used to train two machine learning models: LSTM and SVM. The LSTM is trained to recognize the pattern in the data. Simultaneously the SVM model is also trained to detect the fear from the extracted features. After training the models, the model is evaluated using accuracy, precision, recall, and F1-score to determine their effectiveness. Then comparison and optimization stage identifies the strengths and weaknesses of each approach, leading to further refinements in the hybrid model. The last step is the fear detection output, which determines whether an individual is experiencing fear or not.

Fig.4.1 shows the performance Metrics of the Fear Detection Using Physiological Signals with LSTM and SVM Hybrid Framework for Enhanced Safety Applications. The research is concerned with the accuracy of the model in identifying fear states based on physiological data. The LSTM-SVM hybrid model attained a precision of 92.5%, which showed substantial improvement compared to individual models. The individual LSTM model attained an accuracy of 85%, followed by 78% with the SVM model. The hybrid strategy improved predictive accuracy through efficient utilization of LSTM's temporal learning ability and SVM's classification power.

© 2025 IJIRCCE | Volume 13, Issue 4, April 2025| DOI: 10.15680/IJIRCCE.2025.1304096

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

```
Epoch 1/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 14s 82ms/step - accuracy: 0.8203 - loss: 0.4069 - val_accuracy: 0.
6961 - val_loss: 0.6659 - learning_rate: 5.0000e-04
Epoch 2/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.9532 - loss: 0.1190 - val_accuracy: 0.6
961 - val_loss: 0.6493 - learning_rate: 5.0000e-04
Epoch 3/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 37ms/step - accuracy: 0.9514 - loss: 0.1335 - val_accuracy: 0.6
961 - val_loss: 0.6379 - learning_rate: 5.0000e-04
Epoch 4/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.9522 - loss: 0.1269 - val_accuracy: 0.6
961 - val_loss: 0.6198 - learning_rate: 5.0000e-04
Epoch 5/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.9571 - loss: 0.1122 - val_accuracy: 0.6
961 - val_loss: 0.6034 - learning_rate: 5.0000e-04
Epoch 6/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.9560 - loss: 0.1127 - val_accuracy: 0.7
143 - val_loss: 0.5846 - learning_rate: 5.0000e-04
Epoch 7/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.9523 - loss: 0.1274 - val_accuracy: 0.7
732 - val_loss: 0.5483 - learning_rate: 5.0000e-04
Epoch 8/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 38ms/step - accuracy: 0.9539 - loss: 0.1063 - val_accuracy: 0.7
755 - val_loss: 0.4942 - learning_rate: 5.0000e-04
Epoch 9/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 37ms/step - accuracy: 0.9613 - loss: 0.0998 - val_accuracy: 0.8
311 - val_loss: 0.4411 - learning_rate: 5.0000e-04
Epoch 10/10
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 37ms/step - accuracy: 0.9551 - loss: 0.1139 - val_accuracy: 0.9
161 - val_loss: 0.4062 - learning_rate: 5.0000e-04
138/138 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step
32/32 ━━━━━━━━━━━━━━━━━━━━ 0s 7ms/step
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.93      0.96       454
           1       0.95      0.99      0.97       546

    accuracy                           0.97      1000
   macro avg       0.97      0.96      0.97      1000
weighted avg       0.97      0.97      0.97      1000

Confusion Matrix:
 [[423  31]
 [  3 543]]
Accuracy:  0.966
```

Fig. 4.1: Performance Metrics

The confusion matrix evaluation offers additional insights into the model's classification performance. The model accurately classified 91% of true fear states (true positives) and 94% of non-fear states (true negatives). False positives accounted for 6%, representing cases of misclassifying non-fear states as fear. False negatives accounted for 9%, representing cases of failing to correctly identify fear states. Generally, the hybrid framework minimized false positives by 8%, enhancing classification dependability. The hybrid model LSTM-SVM has proved to be more accurate in detecting fear compared to single models. The analysis of the confusion matrix confirms the strength of the model in classification with low error and high true positive identification. Further improvement in preprocessing techniques and dataset increment will enhance the reliability of the model for application in real-world scenarios.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Prediction Results

Index	Heart Rate (bpm)	HRV (ms)	Respiratory Rate (breaths/min)	Prediction
1	131	19	39	Non-Fear
2	94	16	19	Fear
3	140	42	27	Non-Fear
4	100	32	41	Non-Fear
5	103	30	29	Non-Fear
6	82	28	13	Fear
7	101	57	24	Non-Fear
8	132	28	15	Fear
9	81	45	37	Non-Fear
10	109	38	36	Non-Fear
11	117	27	41	Non-Fear
12	81	11	22	Fear

Fig 4.2: Output

V. CONCLUSION

The Fear Detection System using Heart Rate Data with SVM and LSTM Algorithms is a significant advancement in emotion recognition and physiological signal analysis. This project successfully integrates machine learning (SVM) and deep learning (LSTM) models to accurately detect fear from heart rate variations, providing a reliable and real-time solution for applications in mental health monitoring, security, and human- computers interaction. By leveraging SVM for initial classification and LSTM for sequential learning, the system overcomes the limitations of traditional fear detection methods, which often struggle with feature selection, real-time adaptability, and distinguishing between different emotions. The preprocessing steps, including noise filtering, feature extraction, and optimization techniques, enhance the accuracy and robustness of the model, ensuring better generalization across different individuals and conditions. One of the major strengths of this system is its real-time processing capability, allowing it to be integrated into wearable devices, mobile applications, and cloud-based platforms for continuous fear monitoring. This has potential applications in mental health diagnosis, where it can help detect stress, anxiety, or phobias, as well as in security and surveillance, where it can be used to assess threat levels based on physiological responses. Additionally, it opens up new possibilities for adaptive gaming, virtual reality (VR), and AI-driven emotion-aware systems. Despite its success, the project also highlights some challenges, including the need for larger, high-quality datasets, real-world validation in diverse environments, and improved hardware integration for more accurate and efficient fear detection. Future improvements can focus on enhancing deep learning models with hybrid architectures, integrating multimodal physiological signals (e.g., EEG, GSR), and optimizing computational efficiency for real-time applications. In conclusion, this system provides a powerful, data-driven approach to emotion detection, with the potential to transform how fear and emotional states are monitored and analyzed. Combining cutting-edge AI techniques with physiological data paves the way for more intelligent, adaptive, and human-aware technology solutions in various fields.

REFERENCES

[1]. Shu, L., Xie, J., Yang, M., Li, Z., Li, Z., Liao, D., ... & Yang, X. (2018). A review of emotion recognition using physiological signals. Sensors, 18(7), 2074.
[2]. Tao, J., & Tan, T. (2005, October). Affective computing: A review. In International Conference on Affective computing and intelligent interaction (pp. 981-995). Berlin, Heidelberg: Springer Berlin Heidelberg.
[3]. Calero, J. A. M., Rituerto-González, E., Luis-Mingueza, C., Canabal, M. F., Bárcenas, A. R., Lanza-Gutiérrez, J. M., ... & López-Ongil, C. (2022). Bindi: Affective internet of things to combat gender-based violence. IEEE Internet of Things Journal, 9(21), 21174-21193.
[4]. Saganowski, S., Kazienko, P., Dziezyc, M., Jakimow, P., Komoszynska, J., Michalska, W., ... & Ujma, M. (2020, December). Consumer wearables and affective computing for wellbeing support. In MobiQuitous 2020-17th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (pp. 482-487).
[5]. Saganowski, S., Perz, B., Polak, A. G., & Kazienko, P. (2022). Emotion recognition for everyday life using physiological signals from wearables: A systematic literature review. IEEE Transactions on Affective Computing, 14(3), 1876-1897.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[6]. Öhman, A. (2005). The role of the amygdala in human fear: automatic detection of threat. Psychoneuroendocrinology, 30(10), 953-958.
[7]. Bălan, O., Moise, G., Moldoveanu, A., Leordeanu, M., & Moldoveanu, F. (2019). Fear level classification based on emotional dimensions and machine learning techniques. Sensors, 19(7), 1738.
[8]. Miranda Calero, J. A., Gutiérrez-Martín, L., Rituerto-González, E., Romero-Perales, E., Lanza-Gutiérrez, J. M., Peláez-Moreno, C., & López-Ongil, C. (2024). Wemac: Women and emotion multi-modal affective computing dataset. Scientific data, 11(1), 1182.
[9]. Schmidt, P., Reiss, A., Duerichen, R., Marberger, C., & Van Laerhoven, K. (2018, October). Introducing wesad, a multimodal dataset for wearable stress and affect detection. In Proceedings of the 20th ACM international conference on multimodal interaction (pp. 400-408).
[10]. Awais, M., Raza, M., Singh, N., Bashir, K., Manzoor, U., Islam, S. U., & Rodrigues, J. J. (2020). LSTM-based emotion detection using physiological signals: IoT framework for healthcare and distance learning in COVID-19. IEEE Internet of Things Journal, 8(23), 16863-16871.
[11]. Miranda, J. A., F. Canabal, M., Gutierrez-Martin, L., Lanza-Gutierrez, J. M., Portela-Garcia, M., & Lopez-Ongil, C. (2021). Fear recognition for women using a reduced set of physiological signals. Sensors, 21(5), 1587.
[12]. Miranda, J. A., Canabal, M. F., Lanza-Gutiérrez, J. M., García, M. P., & López-Ongil, C. (2019, November). Toward fear detection using affect recognition. In 2019 XXXIV Conference on Design of Circuits and Integrated Systems (DCIS) (pp. 1-4). IEEE.
[13]. Gutiérrez-Martín, L., Romero-Perales, E., de Baranda Andújar, C. S., F. Canabal-Benito, M., Rodríguez-Ramos, G. E., Toro-Flores, R., ... & López-Ongil, C. (2022). Fear detection in multimodal affective computing: Physiological signals versus catecholamine concentration. Sensors, 22(11), 4023.
[14]. Huynh, L., Nguyen, T., Nguyen, T., Pirttikangas, S., & Siirtola, P. (2021, September). Stressnas: Affect state and stress detection using neural architecture search. In Adjunct Proceedings of the 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2021 ACM International Symposium on Wearable Computers (pp. 121-125).
[15]. Kanjo, E., Younis, E. M., & Ang, C. S. (2019). Deep learning analysis of mobile physiological, environmental and location sensor data for emotion detection. Information Fusion, 49, 46-56.