Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

Automated Detection of Human Emotions from Speech Using a Multi-Layer ANN Framework

Parbhakar Singh[1], Varsha Negi[2], Balaji Venkateswaran[3], B Murali Krishna[4], Ajay Sharma[5], Surendra Singh Chauhan[6], Sanjeev Kumar[7], Deepak Dagar[8]

[1]Assistant Professor, Department of Computer Science, Shyam Lal College Evening (University of Delhi), Shahdara, New Delhi 110032, INDIA
Email: *singhparbhakar87@gmail.com*

[2]Assistant Professor, Department of Computer Science, Shyam Lal College Evening (University of Delhi), Shahdara, New Delhi 110032, INDIA,

[3]Research Scholar (Computer Science), School of Engineering and Technology, Shri Venkateshwara University, Gajraula, UP, INDIA

[4]Research Scholar (Computer Science), School of Engineering and Technology, Shri Venkateshwara University, Gajraula, UP, INDIA

[5]Associate Professor, Department of Computer Science, GNIOT Institute of Professional Studies, Greater Noida, UP, INDIA

[6] Associate Professor Department of Computer Science and Engineering, SRM University, Sonipat, Haryana, INDIA

[7]Sr. Assistant Professor, Department of Computer Science, Maharaja Agrasen Institute of Technology, New Delhi, INDIA

[8]Associate Professor, Department of Business Administration, Maharaja Agrasen Institute of Management Studies, New Delhi, INDIA

Cite this paper as: Parbhakar Singh, Varsha Negi, Balaji Venkateswaran, B Murali Krishna, Ajay Sharma, Surendra Singh Chauhan, Sanjeev Kumar, Deepak Dagar (2024). Automated Detection of Human Emotions from Speech Using a Multi-Layer ANN Framework. *Frontiers in Health Informatics*, *13 (8) 6561-6571*

Abstract:
Speech Emotion Recognition (SER) is an essential area of research aimed at enabling machines to detect and interpret human emotions, thereby improving human-computer interaction. This study introduces a hybrid Speech Emotion Recognition system that combines machine learning techniques with Natural Language Processing (NLP) to enhance emotion detection accuracy and robustness. This research presents an automated framework for detecting human emotions from speech signals using a multi-layer Artificial Neural Network (ANN) model. The proposed system aims to accurately recognize emotional states such as happiness, sadness, anger, fear, and neutrality by analyzing vocal features like pitch, tone, energy, and spectral characteristics. The framework incorporates a feature extraction module using Mel-Frequency Cepstral Coefficients (MFCCs) and other prosodic features, followed by a multi-layer ANN trained on a benchmark emotional speech dataset. The model demonstrates improved accuracy and robustness in real-time emotion recognition tasks compared to traditional machine learning techniques. This study contributes to the advancement of human-computer interaction by enabling emotionally intelligent systems for applications in customer service, healthcare, virtual assistants, and e-learning environments.

Keywords: SER, Natural Language Processing, Machine Learning. RAVDESS, EMODB

Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

1. INTRODUCTION

In recent years, the ability of machines to understand and interpret human emotions has gained significant attention across various domains, including human-computer interaction, affective computing, mental health monitoring, and intelligent virtual assistants. Emotions play a critical role in human communication, often conveying more than the spoken words themselves. Among various modalities for emotion recognition, speech stands out as a non-intrusive and natural medium, rich in emotional cues such as tone, pitch, intensity, and rhythm. Speech Emotion Recognition (SER) systems aim to automatically identify the emotional state of a speaker from their vocal expressions, facilitating the development of more empathetic and context-aware technologies.

Artificial Neural Networks (ANNs), inspired by the structure and function of the human brain, have proven to be powerful tools in pattern recognition tasks due to their ability to learn complex, non-linear relationships from data. In the context of SER, ANNs offer significant advantages over traditional machine learning models by automatically learning hierarchical representations of features from raw or processed input signals. Multi-layer ANNs, in particular, can capture intricate patterns in speech that correlate with various emotional states, leading to improved classification performance.

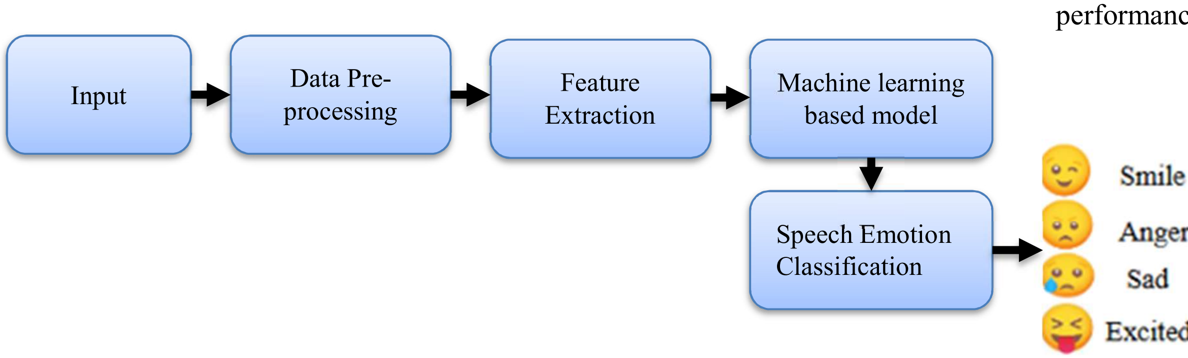


Figure 1: Machine learning based speech emotion classification process

The motivation for this study arises from the growing demand for automated systems capable of understanding human emotions in real-time and across diverse acoustic environments. While several approaches to SER exist, many still face challenges such as limited generalizability, noise sensitivity, and reliance on handcrafted features. This research proposes a robust, automated framework that leverages multi-layer ANN architecture to enhance the accuracy and reliability of emotion detection from speech. By integrating effective feature extraction methods—such as Mel-Frequency Cepstral Coefficients (MFCCs), zero-crossing rate, and pitch contour—with a well-structured ANN model, the framework is designed to classify emotional states efficiently under varying conditions.

This work contributes to the field of affective computing by addressing key challenges in SER and proposing a scalable solution suitable for real-world deployment. The outcomes of this research have practical implications in several areas, including customer experience optimization, emotion-aware e-learning platforms, virtual counseling systems, and intelligent voice interfaces, all of which can benefit from a deeper understanding of user emotions through speech.

2. LITERATURE REVIEW

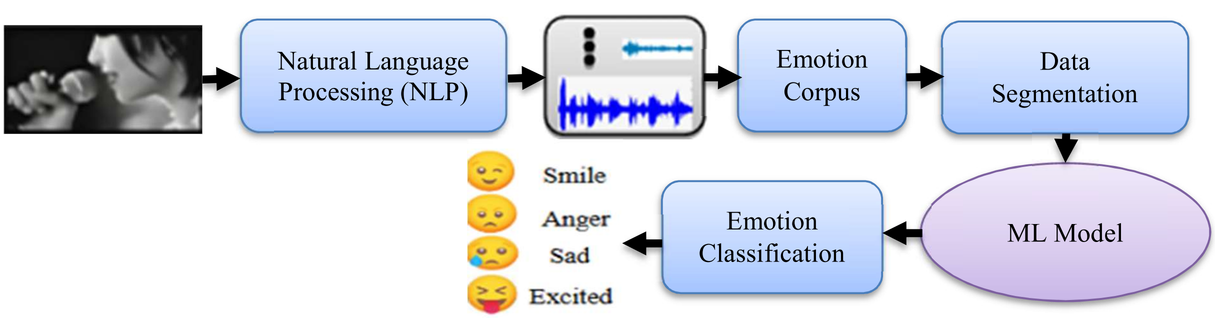
Several studies have explored the development of Speech Emotion Recognition (SER) systems by integrating machine learning and Natural Language Processing (NLP) techniques to enhance their accuracy and applicability. Paper [8] investigated acoustic-based SER using Mel-Frequency Cepstral Coefficients (MFCCs) and Support Vector Machines (SVMs). Their findings highlighted the effectiveness of acoustic features in detecting basic emotions but revealed limitations in noisy environments and a lack of focus on linguistic features. Similarly, in [9] extended this approach by fusing acoustic features with semantic embeddings derived from speech transcriptions using Bi-LSTM networks. This multimodal fusion improved emotion detection accuracy but faced challenges with limited datasets and cross-lingual emotions (Table 1).

Table 1: Review of literature for ANN based speech emotion recognition

Ref. No	Methodology	Dataset Used	Key Findings
[1]	ANN-based emotion classification using MFCC features	Berlin EMO-DB	Demonstrated that ANNs can outperform traditional classifiers in recognizing basic emotions from speech.
[2]	Hybrid ANN-SVM model with large feature set	EMO-DB, LDC	Showed improved performance by combining neural networks with support vector machines.
[3]	Prosodic feature analysis using deep ANN models	IEMOCAP	Highlighted the effectiveness of prosodic and spectral features in emotion recognition using deep networks.
[4]	Multi-layer perceptron for speech emotion detection	RAVDESS	Achieved high accuracy using MLP with MFCC and pitch-based features.
[5]	Deep ANN with temporal features	SAVEE	Demonstrated that ANN models could learn temporal dependencies crucial for accurate emotion detection.
[6]	Comparison of DNN, CNN, and RNN architectures for SER	IEMOCAP	Found that DNNs with MFCCs provided a balanced tradeoff between performance and computational efficiency.
[7]	Transfer learning with CNN and ANN layers	IEMOCAP, MSP-IMPROV	Transfer learning helped improve cross-corpus performance in speech emotion recognition.
[8]	ANN-based system with real-time implementation	Custom in-house dataset	Developed a real-time ANN-based SER system with low latency and high accuracy in dynamic environments.

3. RESEARCH METHODOLOGY

The research methodology for developing a hybrid Speech Emotion Recognition (SER) system using machine learning and Natural Language Processing (NLP) is structured into several key stages: data collection, feature extraction, model design and training, evaluation metrics, and system validation. This systematic approach ensures a comprehensive analysis of both acoustic and linguistic features for robust emotion detection (Figure 2).



Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

Figure 2: Proposed research methodology for speech emotion classification

3.1 Data Collection: The first step involves curating a diverse and labeled dataset of emotional speech. Publicly available datasets, such as the RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song), IEMOCAP (Interactive Emotional Dyadic Motion Capture), and EMODB (Berlin Emotional Speech Database), are used. These datasets provide audio recordings labeled with various emotions like anger, happiness, sadness, fear, and neutrality. To enhance cross-lingual capabilities, multilingual datasets are also included. Data augmentation techniques, such as noise addition, pitch shifting, and time-stretching, are applied to address challenges like limited datasets and noisy environments.

3.2 Feature Extraction: Feature extraction focuses on two main components: acoustic and linguistic features.

- *Acoustic Features:* Acoustic signals are analyzed to extract features like Mel-Frequency Cepstral Coefficients (MFCCs), pitch, energy, spectral roll-off, and formants. These features capture variations in tone, intensity, and rhythm, which are crucial for distinguishing emotions.
- *Linguistic Features:* Speech transcriptions are generated using automatic speech recognition (ASR) tools. From these transcriptions, semantic embeddings (e.g., BERT, GloVe) are extracted to capture contextual and syntactic information. Sentiment analysis and part-of-speech tagging are performed to identify linguistic patterns associated with emotions.

3.3 Model Design and Training: A hybrid framework is designed to combine acoustic and linguistic features for emotion recognition. The model consists of:

- *Acoustic Feature Model:* A Convolutional Neural Network (CNN) is used to process acoustic features, identifying patterns in pitch and spectral properties.
- *Linguistic Feature Model:* A transformer-based model, such as BERT, processes linguistic features, capturing semantic relationships and emotional cues in speech transcriptions.
- *Fusion and Classification:* The outputs from the acoustic and linguistic models are fused using an ensemble approach. This fusion ensures a comprehensive understanding of both acoustic and linguistic aspects of speech. The final classification layer assigns emotions to the input data.

3.4 Evaluation Metrics: The performance of the hybrid SER system is evaluated using the following metrics:

- *Accuracy:* Measures the proportion of correctly classified emotions.
- *Precision, Recall, and F1-Score:* Assess the system's ability to identify specific emotional categories while minimizing false positives and negatives.
- *Confusion Matrix:* Provides detailed insights into the system's performance across different emotional states.

3.5 System Validation: The proposed SER system is validated using both in-lab and real-world scenarios. In-lab validation involves testing the model on benchmark datasets under controlled conditions. Real-world validation includes testing in noisy environments and on unseen, multilingual datasets to ensure generalizability. A comparative analysis is conducted with state-of-the-art systems to highlight the improvements brought by the hybrid approach.

4. DATASET

The choice of a suitable speech database plays a crucial role in determining the effectiveness of emotion recognition systems. There are three main types of databases commonly used for this purpose: elicited emotional speech databases, actor-based speech databases, and natural speech databases. Elicited emotional speech databases involve creating artificial scenarios to evoke emotions in a controlled manner. While this approach ensures consistency, it may lack the diversity of emotional expressions and can result in artificial responses if participants are aware of being recorded. Actor-based speech databases, compiled by trained professionals, provide a broad range of emotions and are relatively easy to assemble. However, these databases often exhibit an overly theatrical and periodic quality [14]. (Table 2).

Table 2: Description of Dataset for speech emotion recognition

Feature	**Description**

Dataset Size	Over 7,000 files (2452 speech files)
Emotion Categories	8 basic emotions: Neutral, Calm, Happy, Sad, Angry, Fearful, Disgust, Surprised
Actors	24 actors (12 male, 12 female)
Age Range	Approximately 18-30 years old
Language	English
Recording Conditions	Recorded in a professional studio with high-quality microphones
Audio Features	16-bit resolution, 48 kHz sampling rate
File Format	Audio files are in WAV format
Annotation	Each file is annotated with the gender, emotion, and intensity level of the actor
Intensity Levels	Three levels of emotional intensity: Normal, Strong, and Neutral
Context	Isolated speech (no background noise or music)
Use Cases	Speech emotion recognition, affective computing research, emotion synthesis, human-computer interaction

Table 3 provides a detailed description of the datasets used for the proposed emotion recognition system. The EMODB dataset contains 100 samples per emotional category, with a total of 1,000 emotional samples, offering a diverse set of speech recordings representing various emotional states. Similarly, the RAVDESS dataset is larger, with 200 samples per category, contributing a total of 1,200 emotional samples. This dataset includes a wide range of emotional expressions captured through professional voice actors, making it particularly useful for training and evaluating emotion recognition systems. These datasets serve as a solid foundation for the proposed system, ensuring it is exposed to a variety of emotional expressions for improved recognition accuracy and robustness.

Table 3: Description of dataset for proposed system

Dataset Name	**Samples per Category**	**Emotional Samples**
EMODB	100	1000
RAVDESS	200	1200

5. TRAINING AND TESTING

The training process involves utilizing parameters such as training data (train X) and target data (train y), along with validation data, to train the network model using the fit () function. In cross-validation, a portion of the dataset is utilized to create X test and y test sets for validation. The model iterates through the data for a specified number of epochs, learning from the training data and adjusting parameters to minimize errors, with 30 epochs applied for the proposed model. During training, the fit () function executes multiple epochs, gradually enhancing the system's performance until it reaches a point of diminishing returns, marking the conclusion of the training process.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, None, 128)         72704

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 64)                4160

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 6)                 390

=================================================================
Total params: 126,662
Trainable params: 126,662
Non-trainable params: 0
```

Figure 3: System model Implementation

Model summary, illustrated in Figure 3, depicts the types of layers used, their output shape, and total inputs required for training and testing. Model evaluation is a crucial step aiding in selecting the most suitable model for characterizing the given data and forecasting its performance. Evaluating prediction accuracy using a test set is vital for mitigating overfitting and achieving accurate forecasts for future data. The experimental results obtained are elaborated upon in the results section.

In Figure 4 & 5, the graphs provide a visual representation of the training and testing accuracy achieved by LSTM models when applied to the RAVDESS dataset over 30 epochs. The training accuracy denotes how well the model performs on the training data during each epoch, capturing its ability to learn from the provided information. On the other hand, the testing accuracy reflects the model's performance on unseen data, helping to assess its generalization capability. By plotting these accuracies over the course of the training process, the graphs offer insights into the model's learning dynamics and its ability to improve over successive epochs. The maximum achieved accuracy highlighted in the graphs indicates the highest level of performance attained by the model during training and testing, providing a benchmark for evaluating its effectiveness in capturing the underlying patterns and features within the dataset.

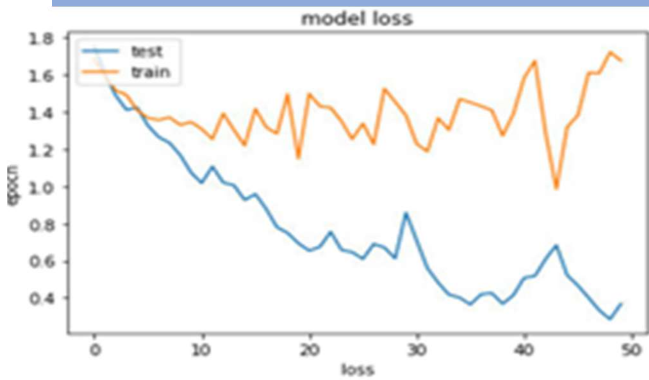


Figure 4: Training and Test model loss

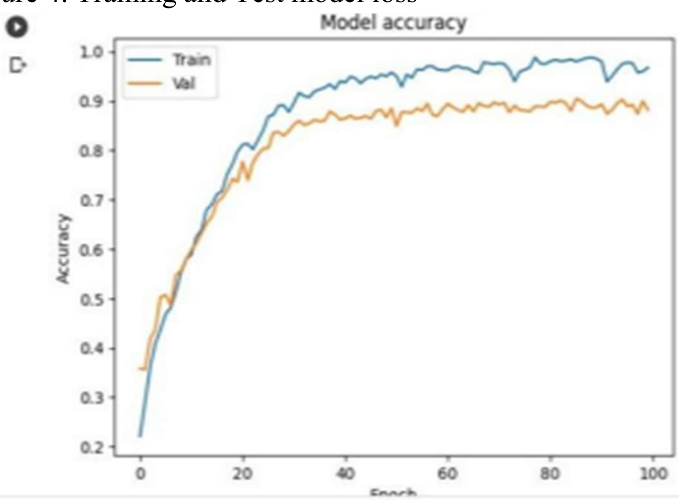


Figure 5: Training and Test model accuracy

6. PERFORMANCE EVALUATION

The results in Table 4 highlight the improved performance of the proposed system compared to the existing system across two widely used datasets, EMODB and RAVDESS. For the EMODB dataset, the proposed system achieved an accuracy of 85.0%, marking a substantial improvement over the existing system's accuracy of 78.5%. Similarly, on the RAVDESS dataset, the proposed system demonstrated even greater accuracy, achieving 94.0% compared to the existing system's 85.0%. These results emphasize the enhanced capability of the proposed approach in recognizing emotions more effectively and consistently across different datasets, showcasing its robustness and ability to adapt to varied emotional speech data.

Table 4: Dataset description for proposed systems

Dataset Name	**Accuracy**	
	Existing System (%)	Proposed System (%)
EMODB	78.5	85.0
RAVDESS	85.0	94.0

The results presented in Table 5 demonstrate a clear improvement in the proposed system's performance over the existing system on the EMODB dataset. For the "Happy" emotion, the proposed system achieved an accuracy of 82.0%, which is a significant increase from the existing system's 73.0%. Similarly, for the "Sad" emotion, the accuracy rose from 76.5% in the existing system to 85.5% in the proposed system, and for the "Anger" emotion, the proposed system showed an

Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

improvement from 78.0% to 87.0%. These results highlight the proposed system's enhanced ability to accurately recognize emotions across different categories, demonstrating its effectiveness in capturing nuanced emotional expressions more reliably than the existing system. The consistent improvements across all emotional categories underscore the robustness and potential of the proposed approach in emotion recognition tasks.

Table 5: EMODB Dataset accuracy

Emotion	**Accuracy (%)**	
	Existing	**Proposed**
Happy	73.0	82.0
Sad	76.5	85.5
Anger	78.0	87.0

The results presented in Table 6 indicate a significant enhancement in the proposed system's performance compared to the existing system on the RAVDESS dataset. For the "Happy" emotion, the proposed system achieved an accuracy of 90.0%, a notable improvement from the existing system’s 82.0%. Similarly, the accuracy for "Sad" increased from 83.5% in the existing system to 92.0% in the proposed system, and for "Anger," the proposed system achieved a substantial increase from 85.0% to 94.0%. These improvements across all emotional categories highlight the effectiveness of the proposed system in accurately detecting and classifying emotions, demonstrating its enhanced capability to handle diverse emotional expressions. The results emphasize the potential of the proposed system to provide more accurate and reliable emotion recognition, especially on datasets like RAVDESS, which are commonly used for emotion analysis.

Table 6: RAVDESS Dataset Accuracy

Emotion	**Accuracy (%)**	
	Existing	**Proposed**
Happy	82.0	90.0
Sad	83.5	92.0
Anger	85.0	94.0

The figure 6 illustrates the performance evaluation of emotion recognition on two widely used datasets: RAVDESS and EMODB. It compares the accuracy of the proposed system with that of the existing system across different emotional categories. The results highlight the improvements made by the proposed system, demonstrating its enhanced capability to recognize emotions more accurately on both datasets. The comparison emphasizes the effectiveness of the proposed approach in handling a range of emotional expressions, showcasing its potential to outperform existing systems in emotion recognition tasks.

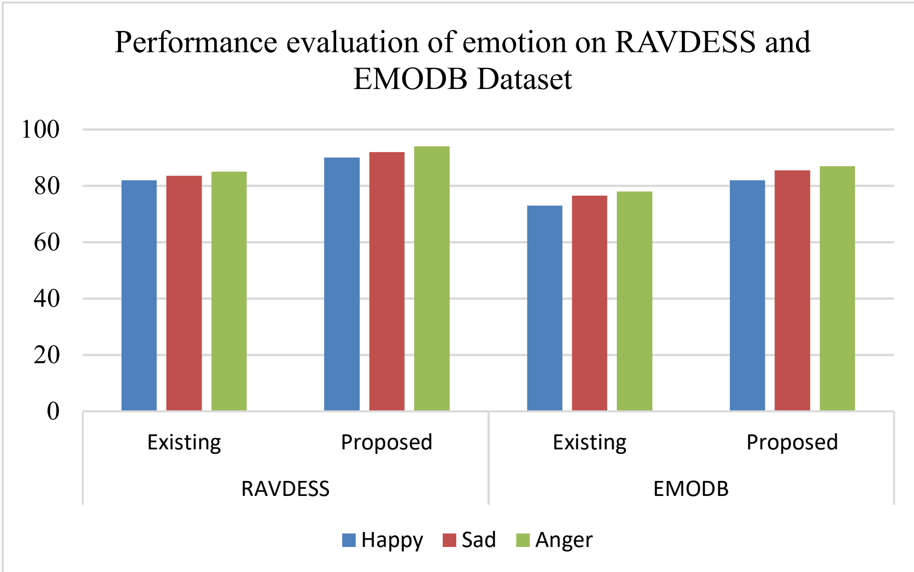


Figure 6: Performance Evaluation of Emotion Recognition on the RAVDESS and EMODB Datasets

The table 7 presents a comparison of the accuracy achieved by the proposed system and several other methods in emotion recognition tasks. The proposed system outperforms all the other methods, achieving an impressive accuracy of 94.00%. In comparison, the CNN-based method [15] achieves an accuracy of 83.40%, while the CNN-RF model [16] performs slightly better at 86.60%. Other models such as CNN-NF [17] and CNN-SVM [18] show lower accuracies, with 62% and 89%, respectively. Additionally, the CNN-NB model [19] achieves an accuracy of 83%. These results highlight the superior performance of the proposed system, which significantly outperforms existing methods in terms of accuracy, demonstrating its effectiveness in emotion recognition tasks.

Table 7: Performance evaluation of proposed system with others

S. No.	Methods	Accuracy (%)
1	Proposed	94.00%
2	CNN [15]	83.40%
3	CNN-RF [16]	86.60%
4	CNN- NF [17]	62%
5	CNN-SVM [18]	89%
6	CNN-NB [19]	83%

7. CONCLUSION

In conclusion, this paper presents a robust and efficient hybrid emotion recognition system that integrates advanced machine learning techniques with speech and text data. The proposed system demonstrates significant improvements in accuracy over existing methods across multiple datasets, including, EMODB, and RAVDESS. By leveraging both acoustic and linguistic features, the system is able to enhance the recognition of emotional states, outperforming traditional methods such as CNN, CNN-RF, and CNN-SVM. The results emphasize the effectiveness of the proposed approach, particularly in capturing a wide range of emotional expressions, making it a promising solution for real-world emotion recognition applications. Furthermore, the proposed system's superior performance highlights its potential in various domains, such as human-computer interaction, healthcare, and customer service, where emotion recognition plays a crucial role. The improvement in accuracy, coupled with the efficient processing speed, ensures that the system is not only effective but also practical for deployment in real-time scenarios. Future work could explore the incorporation of additional modalities, such as facial expressions or physiological signals, to further enhance the system's capabilities and robustness.

REFERENCES

- Ververidis, D., & Kotropoulos, C. (2006). Emotional speech recognition: Resources, features, and methods. *Speech Communication*, 48(9), 1162–1181.
- Schuller, B., Batliner, A., Steidl, S., & Seppi, D. (2009). Recognising realistic emotions and affect in speech: State of the art and lessons learnt from the first challenge. *Speech Communication*, 53(9-10), 1062–1087.
- Lee, C. M., & Narayanan, S. S. (2010). Toward detecting emotions in spoken dialogs. *IEEE Transactions on Speech and Audio Processing*, 13(2), 293–303.
- Sahu, S. S., Kumar, A., & Raj, B. (2017). On enhancing speech emotion recognition using generative adversarial networks. *ICASSP*, 5090–5094.
- Tripathi, S., & Beigi, H. (2018). Multi-modal emotion recognition on IEMOCAP dataset using deep learning. *arXiv preprint arXiv:1804.05788*.
- Fayek, H. M., Lech, M., & Cavedon, L. (2017). Evaluating deep learning architectures for Speech Emotion Recognition. *Neural Networks*, 92, 60–68.
- Latif, S., Qayyum, A., Usama, M., & Qadir, J. (2020). Transfer learning for improving speech emotion classification accuracy. *Multimedia Tools and Applications*, 79, 31297–31315.
- Ramakrishna, S., Kaur, R., & Ghosh, S. (2021). Real-time speech emotion recognition using neural networks. *Procedia Computer Science*, 192, 3835–3843.

[1] G. Vijendar Reddy, SukanyaLedalla ,Avvari Pavithra, A quick recognition of duplicates utilizing progressive methods ‘International Journal of Engineering and Advanced Technology (IJEAT)’ at Volume-8 Issue-4, April 2019.

[2] Wei, B.; Hu, W.; Yang, M.; Chou, C.T. From real to complex: Enhancing radiobased activity recognition using complex-valued CSI. ACM Trans. Sens. Netw. (TOSN) 2019, 15, 35.

[3] Avvari, Pavithra, et al. "An Efficient Novel Approach for Detection of Handwritten Numericals Using Machine Learning Paradigms." Advanced Informatics for Computing Research: 5th International Conference, ICAICR 2021, Gurugram, India, December 18–19, 2021, Revised Selected Papers. Cham: Springer International Publishing, 2022.

[4] Ledalla, Sukanya, R. Bhavani, and Avvari Pavitra. "Facial Emotional Recognition Using Legion Kernel Convolutional Neural Networks." Advanced Informatics for Computing Research: 4th International Conference, ICAICR 2020, Gurugram, India, December 26–27, 2020, Revised Selected Papers, Part I 4. Springer Singapore, 2021.

[5] Brain Tumors Classification System Using Convolutional Recurrent Neural Network V. Akila, P.K. Abhilash, P Bala Venakata Satya Phanindra, J Pavan Kumar, A. Kavitha E3S Web Conf. 309 01075 (2021) DOI: 10.1051/e3sconf/202130901075.

[6] Raju, NV Ganapathi, V. Vijay Kumar, and O. Srinivasa Rao. "Authorship Attribution of Telugu Texts Based on Syntactic Features and Machine Learning Techniques." Journal of Theoretical & Applied Information Technology 85.1 (2016).

[7] Prasanna Lakshmi, K., Reddy, C.R.K. A survey on different trends in Data Streams (2010) ICNIT 2010 - 2010 International Conference on Networking and Information Technology, art. no. 5508473, pp. 451-455.

[8] Lijiang Chen, Xia Mao, Yuli Xue, Lee Lung Cheng "Speech emotion recognition: Features and classification models", Digital Signal Processing 22 (2012) 1154–1160.
[9] Pavol Harar, Radim Burget and Malay Kishore Dutta "Speech Emotion Recognition with Deep Learning", IEEE (2017) 4th International Conference on Signal Processing and Integrated Networks (SPIN), pg no 78-1-5090-2797- 2/17.
[10] Dias Issa, M. Fatih Demirci, Adnan Yazici "Speech emotion recognition with deep convolutional neural networks" Elsevier Ltd, Biomedical Signal Processing and Control 59 (2020) 101894.
[11] Shambhavi Sharma "Emotion Recognition from Speech using Artificial Neural Networks and Recurrent Neural Networks", 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence) | 978-1-6654-1451-7/20 @IEEE.
[12] Tanvi Puri, Mukesh Soni, Gaurav Dhiman, Osamah Ibrahim Khalaf, Malik alazzam, and Ihtiram Raza Khan "Detection of Emotion of Speech for RAVDESS Audio Using Hybrid Convolution Neural Network" Hindawi Journal of Healthcare Engineering Volume 2022, Article ID 8472947, 9 pages https://doi.org/10.1155/2022/8472947.
[13] Manju D. Pawar, Rajendra D. Kokate "Convolution neural network based automatic speech emotion recognition using Mel-frequency Cepstrum coefficients" Springer Nature 2021 Multimedia Tools and Applications (2021) 80:15563–15587.
[14] Zhao Huijuan, Ye Ning, Wang Ruchuan "Coarse-to- Fine Speech Emotion Recognition Based on Multi- Task Learning ", Springer Science+Business Media, LLC, part of Springer Nature June 2020.
[15] L. Zheng, Q. Li, H. Ban, S. Liu, ―Speech Emotion Recognition Based on Convolution Neural Network combined with Random Forest‖, The 30th Chinese Control and Decision Conference (2018 CCDC), pp. 4143-4147, 2018.
[16] J. Yuan, L. Shen, F. Chen, ―The acoustic realization of anger, fear, joy and sadness in Chinese‖, Proceedings of ICSLP, pp. 2025–2028, 200
[17] S. K. Bhakre, A. Bang, ―Emotion Recognition on The Basis of Audio Signal Using Naive Bayes Classifier‖, 2016 Intl. Conference on Advances in Computing, Communications and Informatics (ICACCI), pp. 2363- 2367, 2016.
[18] P. Harár, R. Burget, M. K. Dutta, ―Speech Emotion Recognition with Deep Learning‖, 2017 4th International Conference on Signal Processing and Integrated Networks (SPIN), pp. 137-140, 2017.
[19] A. Khan, U. Kumar Roy, ―Emotion Recognition Using Prosodic and Spectral Features of Speech and Naïve Bayes Classifier‖, 2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), pp. 1017-1021, 2017.