Hubert-LSTM: A Hybrid Model for Artificial Intelligence and Human Speech

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Abstract: — Speech emotion recognition (SER) is a critical component of human-computer interaction, facilitating seamless communication between individuals and machines. In this paper, we propose a hybrid model, integrating Hubert, a cutting-edge speech recognition model, with LSTM (Long Short-Term Memory), known for its effectiveness in sequence modeling tasks, to enhance emotion recognition accuracy in speech audio files. We explore the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) for our investigation, drawn by its complexity and open accessibility. Our hybrid model combines the semantic features extracted by Hubert with LSTM's ability to capture temporal relationships in audio sequences, thereby improving emotion recognition performance. Through rigorous experimentation and evaluation on a subset of actors from the RAVDESS dataset, our model achieved promising results, outperforming existing approaches, with a maximum accuracy of 89.1 %.

Key-words: — artificial intelligence, Hubert, LSTM, machine learning, Speech emotion recognition.

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1. Introduction

Speech emotion recognition (SER) represents a pivotal aspect of human-computer interaction, facilitating rapid and natural communication between individuals and machines. This field holds significant importance in various real-time applications, enhancing human-machine interaction. Researchers are actively engaged in the exploration of speech signals captured through sensors for SER purposes, constituting a dynamic domain within digital signal processing. The primary objective is to discern the emotional state of speakers by analyzing speech signals, which inherently contain rich information beyond mere verbal content [7-10]. Speech represents a complex and richly nuanced form of communication, capable of effectively conveying information [8]. Precise recognition of emotions from speech audio files remains a challenging issue [6] [11] [14] [16] [18]. This challenge is particularly relevant in the context of my paper, where I explore the integration of a hybrid model combining Hubert, a state-of-the-art speech recognition model, with LSTM (Long Short-Term Memory), a type of recurrent neural network known for its effectiveness in sequence modeling tasks. By combining the strengths of both models, we aim to enhance the accuracy and robustness of emotion recognition in speech audio files, addressing the complexities inherent in understanding human emotions from speech signals.

2. Related work

This section reviews significant works in the field of self-supervised speech learning, providing a foundation for the development of the model presented in this study. The wav2vec model was a crucial starting point in this direction, using raw sound to learn useful representations for speech recognition without needing the text labels of the sounds [2]. Advancing this idea, wav2vec 2.0 added a new component: the model learns to differentiate between actual sound and other random sounds, which helps the model to better distinguish important features of speech [7]. Contrastive Predictive Coding (CPC) applied a similar idea across various fields, including audio, relying on the idea that useful information can be obtained by comparing different sections of sound to each other [1]. The HuBERT model combines th-ese previous ideas, learning to predict certain sound patterns in areas where information is hidden (masked), which helps to gain a deeper understanding of the structure and content of speech. Other studies have shown that using deeper networks can improve the model's ability to understand the long and complex context of spoken sounds [3] [20] [21] [24]. Additionally, vq-wav2vec brought an improvement by introducing a layer that transforms sounds into discrete symbols, making the model more efficient and robust [6]. Therefore, these works have contributed to the evolution of speech recognition technologies, each adding new methods to extract information from unlabeled audio data.

Recent advancements also include the application of graph neural networks to speech emotion recognition, which uses feature similarity and LSTM aggregators to enhance model performance and interpretability [5] [12] [13] [15] [17]. This development represents a significant step forward in leveraging complex network architectures for speech analysis, pointing to a broader trend of integrating diverse neural network techniques to improve the depth and accuracy of speech processing models [25-27].

3. Experiment details

For my investigation into emotional speech analysis, I opted for the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS). Two pivotal factors influenced this decision. Firstly, RAVDESS is an open-source dataset, promoting accessibility and fostering collaboration within the scientific community. Its availability fosters transparency and reproducibility in emotional speech anal-ysis research. Secondly, the dataset's complexity presented an intriguing challenge. Researchers have encountered difficulties achieving high performance on RAVDESS, piquing my interest. The dataset's diverse range of emotional expressions and nuanced intensity levels offers a unique opportunity to contribute to the refinement and advancement of emotional analysis methods in speech.

The RAVDESS database is a validated multimodal

repository designed for the analysis of emotional speech and song. It features a gender-balanced cohort of 24 professional actors delivering lexically-matched statements in a neutral North American accent. The speech component covers emotions such as calm, happiness, sadness, anger, fear, surprise, and disgust. Each emotion is presented at two intensity levels, supplemented by a neutral expression. This comprehensive dataset serves as a solid foundation for in-depth emotional analysis. In this research, the focus was exclusively on the emotional speech component, aiming for classification [4] [19] [20] [23].

The dataset comprises 1440 files, each uniquely identified by a filename consisting of seven parts. The data loading process utilizes the os.listdir() function to iterate through the directory specified by the *audiodir* variable. Files with the .wav extension are identified and added to the appropriate lists of paths based on the dataset's distribution. Labels are assigned using predefined criteria extracted from the filenames, which encode information about modality, vocal channel, emotion, intensity, statement, repetition, and actor.

Exemple of audio file - (02-01-06-01-02-01-12.wav):

• Modality (01 = full-AV, 02 = video-only, 03 = audio-only).

• Vocal channel (01 = speech, 02 = song).

• Emotion (01 = neutral, 02 = calm, 03 = happy, 04 = sad, 05 = angry, 06 = fearful, 07 = disgust, 08 = surprised).

• Emotional intensity (01 = normal, 02 = strong). There is no strong intensity for the 'neutral' emotion.

• Statement (01 = Kids are talking by the door, 02 = Dogs are sitting by the door).

• Repetition (01 = 1st repetition, 02 = 2nd repetition).

• Actor (01 to 24. Odd-numbered actors are male, even-numbered actors are female).

Torchaudio library is employed to load and convert audio files into tensor representations. The audio signals undergo transformations, including conversion to mono and resampling to ensure a standardized sampling rate of 16000 Hz. Feature extraction is performed using the Wav2Vec2 processor, facilitating effective analysis and interpretation by the subsequent model. The Wav2Vec2 processor, a robust creation by Facebook AI Research, serves as an invaluable asset for feature extraction from audio signals [2]. With its capabilities, it empowers the extraction of crucial features from audio signals, meticulously preparing the data for further analysis with machine learning models. This processor can be easily imported and used in the Python environment using the Hugging Face Transformers library.

4. Proposed research

Speech emotion recognition (SER) is pivotal for voice assistance and human-machine interfaces. This study explores different approaches for emotion recognition using the Hubert model, focusing on the RAVDESS dataset. Three scenarios were analyzed, all employing the same pre-trained Hubert model, with variations including data augmentation and the integration of a hybrid Hubert-LSTM model. Google Colab Pro was exclusively utilized for training, leveraging its advanced resources, including a TPU backend, 35 GB of system RAM, and a 225.8 GB disk memory. The integration of a TPU backend from Google Compute Engine significantly accelerated Python code execution, particularly in machine learning tasks.

5. Classic Hubert with Wav2Vec2 processor (no augmentation)

In the quest to unveil the secrets of emotions expressed in human vocal discourse, we embraced an advanced approach - fine-tuning the HuBERT model, a cutting-edge product developed by researchers in artificial intelligence.This intricate process of tailoring the model to the specifics of our dataset was meticulously orchestrated to reveal the nuances of emotional expression in voice.

Hidden-Unit BERT (HuBERT) is an approach for self-supervised speech representation learning, based on techniques similar to those used in the BERT (Bidirectional Encoder Representations from Transformers) model but adapted for processing audio signals. Essentially, HuBERT uses an offline clustering step to provide aligned target labels for a prediction loss similar to that in BERT. A key feature of HuBERT is applying the prediction loss only to masked regions in the audio signal, forcing the model to learn a combined representation of acoustic and linguistic models for continuous speech inputs. This approach relies primarily on the consistency of the unsupervised clustering step rather than the quality of the cluster labels assigned. HuBERT has demonstrated comparable or improved performance compared to other models such as wav2vec 2.0 on various speech datasets, including Librispeech and Libri-light. Using models with a large number of parameters, HuBERT has achieved significant reductions in speech error rates on challenging evaluation subsets [3]. The HuBERT model was trained on vast unsupervised speech datasets like LibriSpeech and Libri-light, which contain 960 and approximately 60,000 hours of speech recordings, respectively. These datasets offer diverse speech content, including various accents and styles, ideal for training self-supervised learning models. While HuBERT's concepts can be implemented in libraries like PyTorch or TensorFlow, specific details about a „HuBERT model in Python" depend on its implementation and training dataset.

HuBert with Wav2Vec2 model utilizes the pre-trained Hubert architecture, and in the fine-tuning process (additional training of the model on specific data), it employs frozen weights of the pre-trained Hubert model. This means that the layers of the neural network composing the pre-trained Hubert model are not updated during training on the RAVDESS dataset but are kept constant. Instead, an additional classification layer is added, initialized randomly, and trained to adapt to recognizing emotions from audio speech. This additional classification layer consists of a fully connected layer followed by a dropout layer for regularization and then an output layer that produces emotion predictions. During training, only the parameters of this additional classification layer are updated, while the parameters of the pre-trained Hubert model remain unchanged. This method is efficient for leveraging the pre-trained knowledge of the Hubert model and adapting it to a specific task, such as recognizing

emotions from speech audio, without needing to train the entire model from scratch. Thus, we benefit from transfer learning, which can lead to better results with less training effort (see fig.1 HuBert with Wav2Vec2 processor).

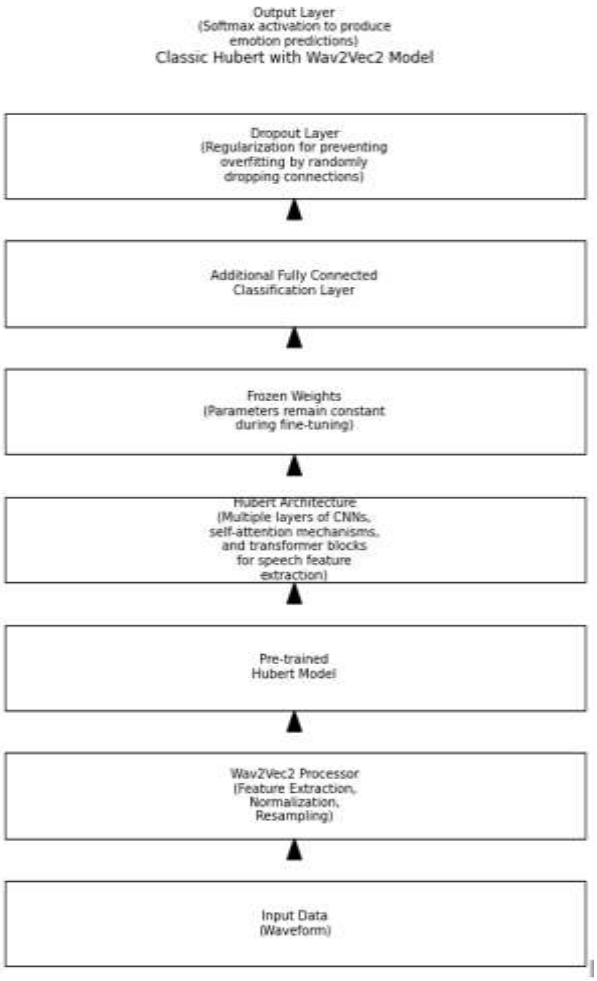

Figure 1. HuBert model

6. Classic Hubert with Wav2Vec2 processor (augmentation)

The second model, data augmentation is applied by adding Gaussian white noise to the audio signals. This type of augmentation adds a small amount of random noise to the original audio signals, thus simulating the natural variability of the data. Gaussian white noise is a type of random noise with a normal distribution, meaning that the levels of added noise are drawn from a normal distribution with a certain mean and standard deviation. This augmentation technique can be useful in various machine learning tasks for audio signal processing. Adding a controlled level of noise can help increase the model's generalization, making it more robust to variability in the test data and reducing the risk of overfitting on the training data. Additionally, it can help enhance the model's robustness to real-world noise in the environment where it will be used.

7. HuBert-LSTM

By combining the pre-trained Hubert architecture with recurrent neural networks (LSTM), we have created a hybrid model that integrates the semantic features extracted by Hubert with the LSTM's ability to capture temporal relationships in audio sequences. Within the LSTM model, we used a single bidirectional LSTM layer with a hidden size of 256 units. This bidirectional LSTM layer allows the model to explore temporal information in both directions of the audio sequence, thereby enhancing its ability to learn complex temporal relationships. By jointly training these two components, the model becomes capable of understanding the temporal context of emotions and extracting relevant semantic features, leading to improved performance in the task of emotion recognition from audio signals.

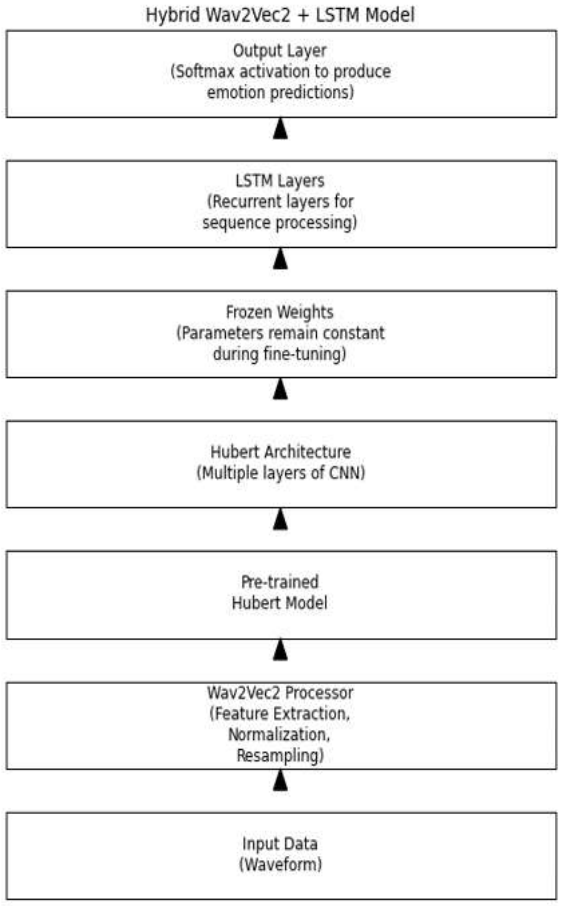

Figure 2. HuBert-LSTM

In the hybrid model, the Wav2Vec2 processor is utilized to process the raw audio signals, extracting high-level features. These features, along with the pre-trained weights from the Hubert model, are then passed through additional LSTM layers. These LSTM layers analyze the temporal dynamics of the audio sequences, capturing long-term dependencies and temporal patterns. By incorporating both the semantic features extracted by Wav2Vec2 and the pre-trained weights from Hubert into the LSTM layers, the model can effectively learn and represent the complex relationships between the audio features and the corresponding emotion labels. This integration of different components allows the hybrid model to leverage the

strengths of each architecture, ultimately enhancing its performance in emotion recognition tasks.

8. Results and discussion

To achieve precise accuracy on the RAVDES audio data, we divided the 24 actors as follows: 20 actors for the training set, 2 actors for the validation set, and 2 actors for testing. Each folder representing an actor and contains a total of 60 audio files. There are 8 files for each of the 7 classes of emotions and 4 audio files for the neutral class. In total, there are 24 actors, resulting in a simple calculation of 1440 audio recordings (60x24).This is crucial because by using new actors in the testing set, the model will demonstrate how well it classifies new data that has not been used in the training and validation processes before. Furthermore, we trained the model 12 times, rotating the actors each time to ensure that all actors go through the training, validation, and testing processes, thus avoiding subjectivity in the classification process. In the table 1, we exemplify the results on the testing set obtained from rotating the actors for each individual model. During the evaluation on the test set, the Hubert model achieved a maximum score of 0.833, while the Hubert model with data augmentation (Hubert-aug) performed the best, with a score of 0.841. Similarly, the model combining Hubert with LSTM layers (Hubert-LSTM) achieved the highest score of 0.891. The best results, as mentioned, occurred with the pair of actors Actor_07 and Actor_08, and on the opposite, the poorest results were generated with the pair Actor_13 and Actor14 (see line 6- of table 1).

TABLE I. RESULTS ON 12 FOLDS

ID	Hubert	Hub-aug	Hub-LSTM	Training Data	Validation Data	Test Data
1	0.691	0.775	0.792	Actor_04: Actor 24	Actor_01, Actor_02	Actor_03, Actor_04
2	0.771	0.824	0.842	Actor_02+ Actor 06: Actor_24	Actor_03, Actor_04	Actor_05, Actor_06
3	0.833	0.841	0.891	Actor_04+ Actor 08: Actor_24	Actor_05, Actor_06	Actor_07, Actor_08
4	0.574	0.641	0.641	Actor_06+ Actor 10: Actor_24	Actor_07, Actor_08	Actor_09, Actor_10
5	0.775	0.683	0.783	Actor_08+ Actor 12: Actor_24	Actor_09, Actor_10	Actor_11, Actor_12
6	0.566	0.541	0.616	Actor_10+ Actor 14: Actor_24	Actor_11, Actor_12	Actor_13, Actor_14
7	0.591	0.625	0.675	Actor_12+ Actor 16: Actor_24	Actor_13, Actor_14	Actor_15, Actor_16
8	0.750	0.700	0.741	Actor_14+ Actor 18: Actor_24	Actor_15, Actor_16	Actor_17, Actor_18
9	0.708	0.700	0.700	Actor_16+ Actor 20: Actor_24	Actor_17, Actor_18	Actor_19, Actor_20
10	0.666	0.708	0.750	Actor_18+ Actor 22: Actor_24	Actor_19, Actor_20	Actor_21, Actor_22
11	0.708	0.716	0.683	Actor_20	Actor_21, Actor_22	Actor_23, Actor_24
12	0.714	0.705	0.705	Actor_02: Actor 22	Actor_23, Actor_24	Actor_01, Actor_02
13	0.696	0.705	0.735	⇦ average		

These results suggest that adding LSTM layers significantly improves the model's performance, resulting in more accurate predictions on the test dataset. There is variation in the performance of the models across different groups of actors, which may indicate the influence of individual actor characteristics on model performance. In the table 1, on line 13, the average of the results obtained by rotating each pair of axes can be observed, ensuring that all actors go through the testing, validation, and training process. The HuBert model without augmentation achieved an average of 0.696, while the augmented model obtained an average of 0.705, approximately 1 percent better. The Hybrid HuBert with LSTM model stands out significantly, achieving a score of 0.735 on the RAVDES dataset, approximately 3 percent more than the augmented model and 4 percent more than the classic model without augmentation. This highlights the importance of the hybrid model in emotion classification, making it a powerful model. Compared to article [1], which utilized a hybrid LSTM-Transformer model on the same RAVDES dataset, my hybrid model achieved better performance on the test set. In that article, an average performance of 69.61% was obtained, which is 4 percentage points lower than my hybrid model. Additionally, in article [1], the cross-validation method using 10 folds was employed, where 10% of each emotion was kept for the test set. I find this approach incorrect because new actors should be used for the test set to observe how the model performs. Therefore, the performance of 69.61%, it is considered less realistic. In the figure 3, we depicted a graph highlighting the number of correctly interpreted classifications (on the test dataset) relative to each emotion class, representing the highest accuracy of the Hubert-LSTM system. As observed in the figure 3, the model performed best on the emotions angry and fearful3, with all 16 correctly predicted recordings out of 16. On the other end of the spectrum lies the neutral class, where the model predicted 4 out of 8 audio files (50%). In Figure 4, three graphs can be observed, highlighting the performances of the HuBert-LSTM model on the training dataset and validation dataset, wich represents acuracy and the loss function.

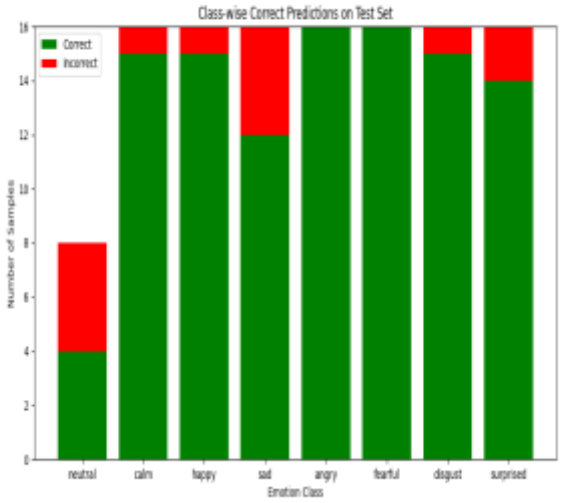

Figure 3. Predictions on best fold Hubert-LSTM

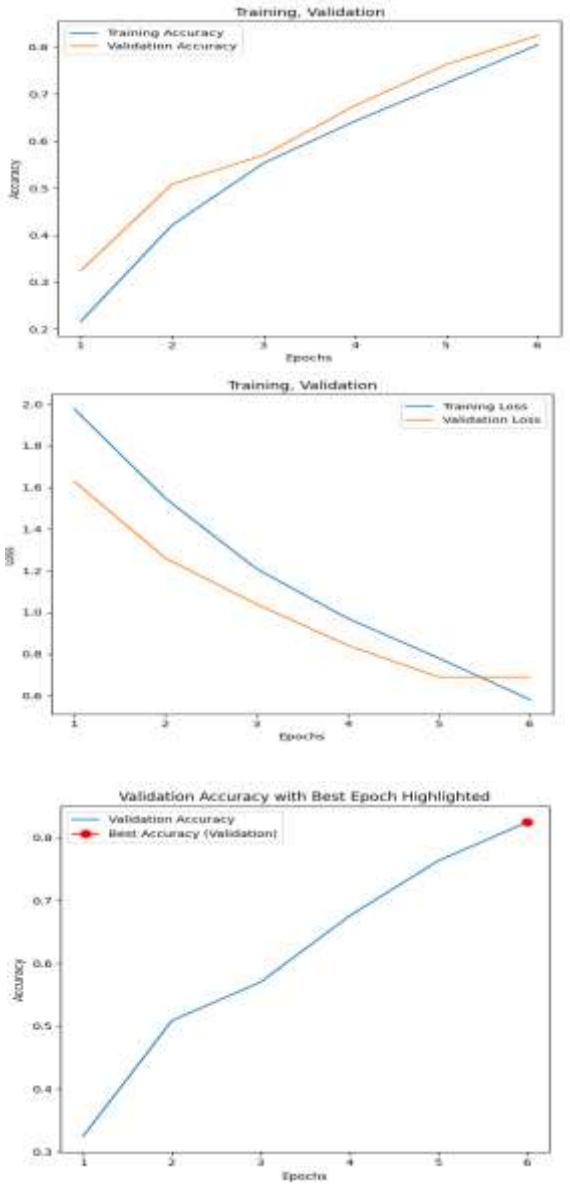

Figure 4. Performance on best fold HuBert-LSTM (graphic representation)

On the graph highlighting the performance on the validation dataset , it reveals that the highest score is achieved at epoch 6, representing an accuracy of 82.45%. In table 2, we highlighted the performances on the test, validation, and training datasets to illustrate their differences across epochs. It is evident that the highest accuracy was achieved on the test set, reaching 89.1%. Conversely, on the training and validation sets, the best performance was encountered at epoch 6, with an accuracy of 80.5% on the training set and 82.4% on the validation set. These findings suggest that the model demonstrates good generalization ability, yielding better results on new, unseen data (test set) com-pared to the data used for training and validation. As indicated in Table 2, the columns for test accuracy and test loss each contain a single value. This occurs because the model was tested on data that were not utilized during the training or validation phases. Consequently, the test dataset was applied only after the completion of six epochs.

The low values of the loss functions (table 2) across all sets training, validation, and testing, are significant for assessing the model's performance. On the training set, the loss function reached a minimum value of 0.580, indicating the model's ability to adapt well to the training data and make precise predictions. Similarly, on the validation set, the loss function obtained a value of 0.688, suggesting adequate agreement between the model's predictions and the - the testing set, the loss function recorded the lowest value of 0.459, indicating excellent generalization capability of the model to make accurate predictions on unseen data. These results are encouraging, suggesting that the model is efficient and generalizable, demonstrating consistent performance across various datasets. However, it is essential to continue monitoring and evaluating the model's performance to identify and address any potential issues or discrepancies.

TABLE II. PERFORMANCE ON BEST FOLD HUBERT-LSTM (VALUE REPRESENTATION)

Epoch	Train Accuracy	Validation accuracy	Train loss	VALIDATION Loss	Test accuracy	Test Loss
1	0.216	0.324	1.975	1.627	0.891	0.459
2	0.421	0.508	1.546	1.259		
3	0.553	0.570	1.208	1.038		
4	0.642	0.675	0.970	0.840		
5	0.723	0.763	0.779	0.6881		
6	0.805	0.824	0.580	0.689		

According to the confusion matrix represented in figure 5 (best model HuBert-LSTM), to assess the effectiveness of the emotion classification model, various standard metrics such as precision, recall, and the F1 score were employed. Precision, calculated as the ratio of true positives (TP) to the sum of true positives and false positives (FP), measures the accuracy of the model's predictions for each emotion.

Mathematically, precision is represented as:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

Recall, also known as sensitivity, quantifies the model's ability to correctly identify positive instances from the total actual positives by dividing TP by the sum of TP and false negatives (FN). It is expressed as:

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1\ Score = 2(PrecisonXRecall)/(Precison + Recall) \quad (3)$$

F1 score, the harmonic mean of precision and recall, offers a balanced assessment of the model's performance. It is computed using the formula F1 overall accuracy of the model, reflecting the ratio of total correct predictions to total predictions made, provides a comprehensive measure of its performance across all emotions. Therefore, the combination of these metrics allows for a thorough evaluation of both individual emotion classification and the model's overall efficacy. The evaluation metrics provide a comprehensive overview of the emotion classification model's performance across various emotions. For the „Neutral" category, the model achieved a precision of 80%, indicating that 80% of the predictions made for Neutral were correct. However, the recall rate for Neutral was 50%, suggesting that only half of the actual Neutral instances were captured by the model. Consequently, the F1 Score, which considers both precision and recall, settled at 61.54%, representing a balanced measure of the model's effectiveness in classifying Neutral emotions. Moving to the „Calm" emotion, the model demonstrated a precision of 78.95% and a recall of 93.75%, resulting in an F1 Score of 85.71%, indicative of a strong performance in identifying Calm emotions. Similarly, for the „Happy" category, the model exhibited a precision of 71.43%, a recall of 93.75%, and an F1 Score of 81.08%, reflecting satisfactory performance in recognizing Happy emotions. The „Sad" emotion showcased perfect precision at 100%, with a recall rate of 75%, leading to an F1 Score of 85.71%, indicating a robust overall performance for Sad emotions. In the case of „Angry" emotions, the model demonstrated high precision (94.12%) and perfect recall (100%), resulting in an outstanding F1 Score of 96.97%. Furthermore, for „Fearful" and „Disgust" emotions, the model achieved perfect precision, recall, and F1 Score, indicating exceptional performance in identifying these emotions. Lastly, for „Surprised" emotions, the model exhibited a precision of 93.33%, a recall of 87.5%, and an F1 Score of 90.32%, highlighting a strong capability in recognizing Surprised emotions. The overall model performance, measured by accuracy, was found to be 89.17%, underscoring the model's effectiveness in classifying emotions across the dataset.

These metrics collectively provide valuable insights into the model's strengths and areas for potential refinement. In addition to the evaluation of individual emotion categories, it's worth highlighting the robustness of the model's performance across various scenarios. The utilization of a diverse dataset encompassing a wide range of emotions and expressions ensures that the model is trained to generalize well to real world scenarios. Moreover, the incorporation of advanced architectures such as HuBert-LSTM contributes to the model's adaptability and ability to capture nuanced patterns within the data. This adaptability is particularly crucial in emotion recognition tasks where subtle variations in facial expressions, tone of voice, and contextual cues play a significant role. Furthermore, the high accuracy and precision achieved across most emotion categories underscore the model's potential for practical applications in fields such as affective computing, human-computer interaction, and sentiment analysis. Overall, the comprehensive evaluation metrics coupled with the model's adaptability and performance across diverse emotional contexts demonstrate its efficacy and potential for real-world deployment. Continued research and refinement in this domain hold promise for further enhancing the model's capabilities and advancing the field of emotion recognition.

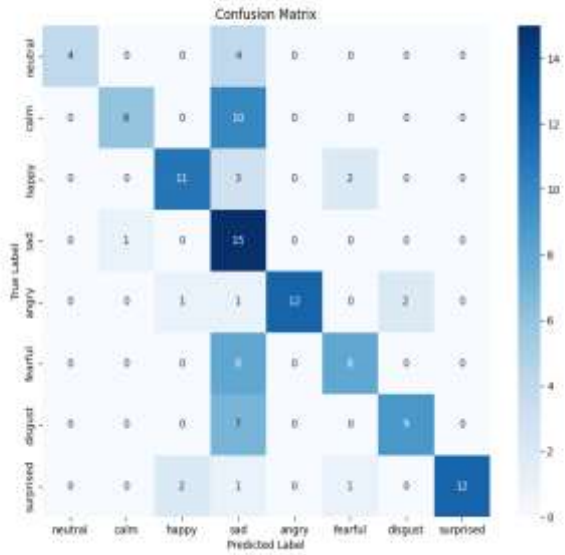

Figure.5. Confusion Matrix HuBert-LSTM on best fold

The graphical depiction in Figure 6, showcasing the performance of the best model, Hubert-augmentation, delineates the accuracy of predictions across different emotion categories. Notably, in the „Neutral" category, the model achieves a moderate performance, correctly predicting 4 out of 8 examples, while misclassifying the remaining 4. Conversely, the „Calm" emotion exhibits outstanding performance, with 15 out of 16 examples accurately predicted, showcasing the model's robust capability in this category. Similarly, the „Fearful" and „Disgust" emotions demonstrate high precision, with 15 out of 16 examples correctly classified. On the other hand, the „Surprised" category presents a notable challenge for the model, with only 11 out of 16 examples predicted correctly. Overall, the graph suggests that the model excels particularly well in classes such as „Calm," „Fearful" and „Disgust" while facing difficulties in accurately classifying instances of „Neutral" and „Surprised" emotions.

According to the graphs depicted in Figures 3 and 6, it can be observed that the HuBert-LSTM model performed significantly better on the „angry" emotion, correctly classifying all 16 examples, compared to the HuBert-

augmentation model, which classified 13 out of 16 examples correctly. Additionally, the HuBert-LSTM model demonstrated superior performance on the happy" emotion (15 out of 16 compared to 13 out of 16), „fearful" emotion (16 out of 16 compared to 15 out of 16), and "surprised" emotion (14 out of 16 compared to 11 out of 16). The HuBert-augmentation model generalized better only on the „sad" emotion (15 out of 16 compared to 12 out of 16).

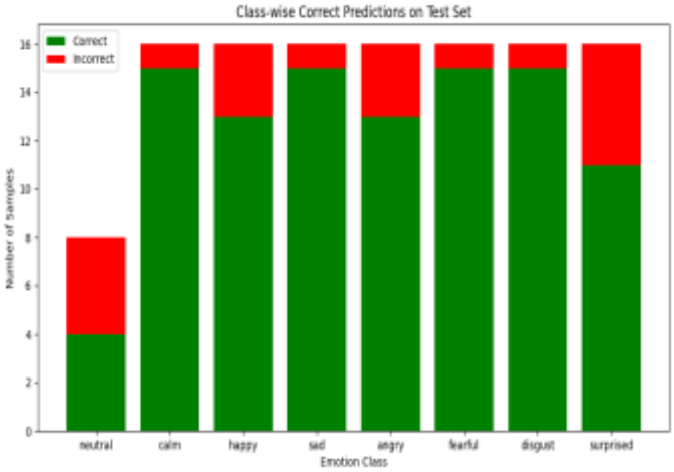

Figure 6. Predictions on best fold Hubert-augmentation

In the analysis of the performance of the HuBert-augmentation and HuBert-LSTM models, significant differences in their graphical behavior are noticeable, reflecting variations in accuracy and stability. Figure 7 illustrates a graphical representation of the performance of the HuBert-augmentation model, while figure 4 depicts the performance of the HuBert-LSTM model. A notable observation is the more linear character of the graph associated with the HuBert-LSTM model, as opposed to the evident fluctuations in the case of the HuBert-augmentation model, as analyzed in the table 3.

TABLE III. PERFORMANCE ON BEST FOLD HUBERT-AUGMENTATION (VALUE REPRESENTATION)

Epoch	Train Accuracy	Validation accuracy	Train loss	Validation Loss	Test accuracy	Test Loss
1	0.274	0.385	1.843	1.378	0.841	0.625
2	0.502	0.622	1.291	1.150		
3	0.621	0.719	1.010	0.687		
4	0.777	0.763	0.678	0.619		
5	0.793	0.859	0.578	0.499		

Throughout the evaluation of the models, relevant performance metrics were identified. Thus, the HuBert-augmentation model achieved an accuracy of 79.3% on the training set, 85.9% on the validation set, and 84.1% on the test set. In contrast, the HuBert-LSTM model demonstrated superior performance on the test set, recording an accuracy of 89.1%. This indicates better adaptability of the HuBert-LSTM model to the test data compared to the augmented model. Additionally, a significant improvement in the loss function on the test set of the HuBert-LSTM model is noteworthy, which registered a value of 0.45 compared to 0.62 for the hybrid model. These differences underscore the superior efficiency and robustness of the HuBert-LSTM model compared to the augmented variant, suggesting better adaptation to test data and enhanced generalization capabilities.

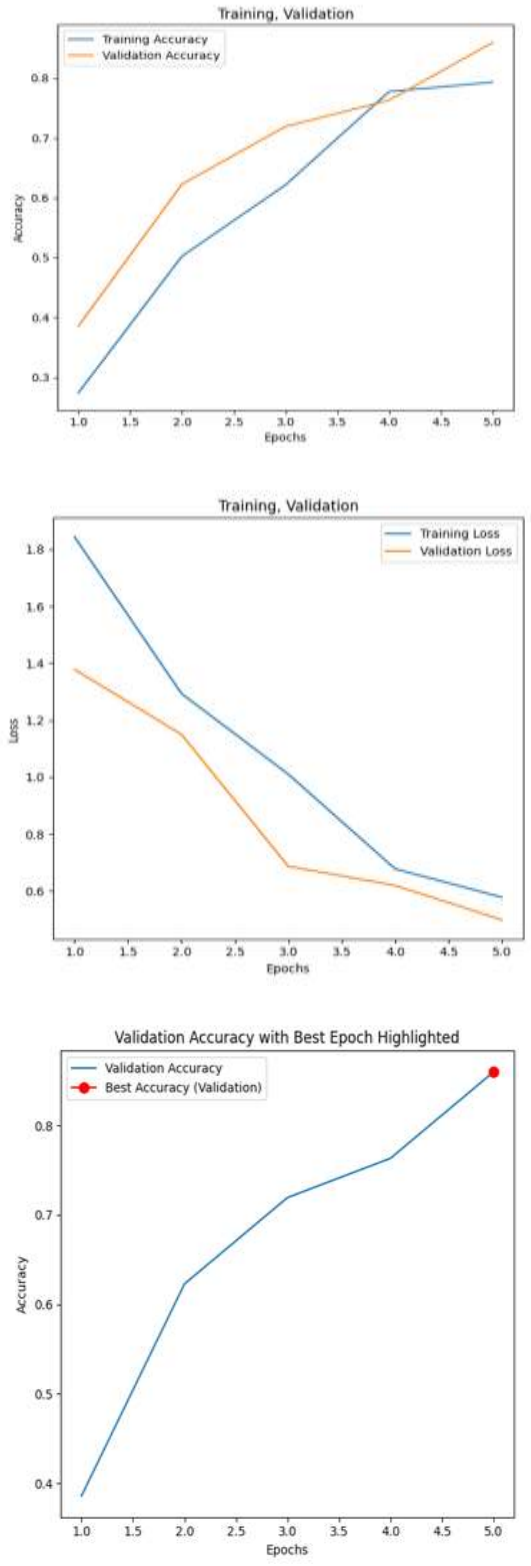

Figure 7. Performance on best fold HuBert-augmentation (graphic representation)

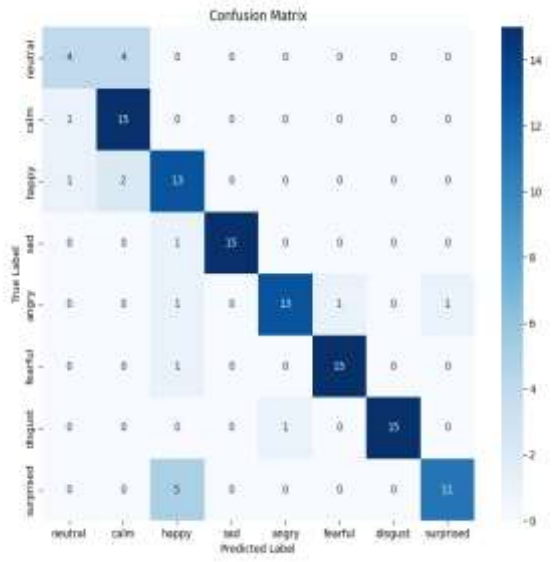

Figure 8. Confusion Matrix HuBert-augmentation on best fold

Upon analyzing the confusion matrix depicted in the Figure 8, we derived the subsequent performance metrics: In the ,,Neutral" category, precision reached 66.67% with a sensitivity of 50.00%, resulting in an F1 score of 57.14%. Conversely, for expressions denoting ,,Calm" and ,,Sadness," results improved significantly, achieving precisions of 57.69% and 93.75%, respectively. Sensitivities for ,,Calm" and ,,Sadness" were also notable at 93.75%, yielding F1 scores of 71.43% and 93.75%, respectively.

Noteworthy is the robust performance observed in emotions such as "Happy," "Fearful," "Dis-gust," and "Surprised," with precisions ranging from 86.67% to 93.75%, sensitivities between 68.75% and 93.75%, and F1 scores between 78.57% and 93.75%.

A detailed analysis of the performance of the emotion classification models, HuBert-LSTM and HuBert-augmentation, reveals significant differences in their effectiveness. Regarding the HuBert-LSTM model, it demonstrates higher precision compared to HuBert-augmentation for most emotions, such as Neutral (80% vs. 66.67%), Calm (78.95% vs. 57.69%), and Happy (71.43% vs. 86.67%). The F1 scores of the HuBert-LSTM model are also generally higher for these emotions compared to those of the HuBert-augmentation model. However, the HuBert-augmentation model achieves higher recall rates (sensitivity) for certain emotions, such as Sad (93.75% vs. 75%), Fearful (93.75% vs. 100%), e and Disgust (93.75% vs. 100%), compared to HuBert-LSTM. This suggests that HuBert-augmentation may excel in capturing specific emotions but at the cost of lower precision. Overall, despite the higher performances of HuBert-augmentation in some cases, HuBert-LSTM appears to provide a more precise and balanced classification of emotions, thus highlighting the advantages and limitations of each model in tackling this complex task. Additionally, when considering emotions such as Angry, Fearful, Disgust, and Surprised, both models exhibit strong performances, with precision ranging from 86.67% to 93.75% and sensitivities between 68.75% and 100%. However, while HuBert-LSTM maintains perfect precision for Sad emotions, achieving 100%, HuBert-augmentation surpasses it in terms of sensitivity, with a notable 93.75%. This discrepancy underscores the nuanced differences in how each model handles specific emotional nuances within the dataset. Moreover, the overall accuracy of the models, a critical measure of their effectiveness in classifying emotions across the entire dataset, reinforces HuBert-LSTM's superiority, standing at an impressive 89.17% compared to HuBert-augmentation. Despite these differences, both models provide valuable insights into the landscape of emotion classification, illuminating areas for further refinement and optimization in future iterations. Furthermore, delving deeper into the intricacies of model performance reveals intriguing patterns. For instance, while HuBert-LSTM showcases remarkable precision across a spectrum of emotions, HuBert-augmentation excels in capturing subtle variations in emotional expressions, particularly evident in its higher sensitivity rates for certain categories. This nuanced interplay between precision and recall highlights the complex trade-offs inherent in emotion classification tasks. Additionally, the disparity in performance metrics underscores the need for a comprehensive evaluation framework that considers not only overall accuracy but also the model's ability to discern between nuanced emotional states. As advancements in natural language processing continue to evolve, leveraging these insights will be crucial in refining emotion classification models to better serve diverse applications, from sentiment analysis to affective computing. In the table 4, the performance of the HuBert-noaugmentation model on the training, validation, and test sets is presented. During training, there is a progressive improvement in accuracy, with a significant increase from 27.25% in the first epoch to 84.5% in the fifth epoch. On the validation set, the model continues to show improvements, reaching an accuracy of 85.96% in the same epoch. On the test set, the model also achieves solid results, with an accuracy of 83.3%. Regarding loss, there is a notable decrease, reaching a value of 0.41 on the test set, indicating the model's ability to adapt well and make accurate predictions.

TABLE IV. PERFORMANCE ON BEST FOLD HUBERT-NOAUGMENTATION (VALUE REPRESENTATION)

Epoch	Train Accuracy	Validation accuracy	Train loss	Validation Loss	Test accuracy	Test Loss
1	0.272	0.5	1.8426	1.317		
2	0.545	0.578	1.249	1.182		
3	0.675	0.728	0.888	0.825	0.833	0.411
4	0.768	0.763	0.643	0.694		
5	0.845	0.859	0.466	0.504		

These results underscore the reliability and effectiveness of the HuBert-noaugmentation model in audio data classification tasks.

In the figure 9, we graphically highlighted the performances achieved on the training and validation sets by the HuBert-noaugmentation model for each epoch. It is worth mentioning that the model was trained up to the fifth epoch, as beyond this point we encountered overfitting issues.

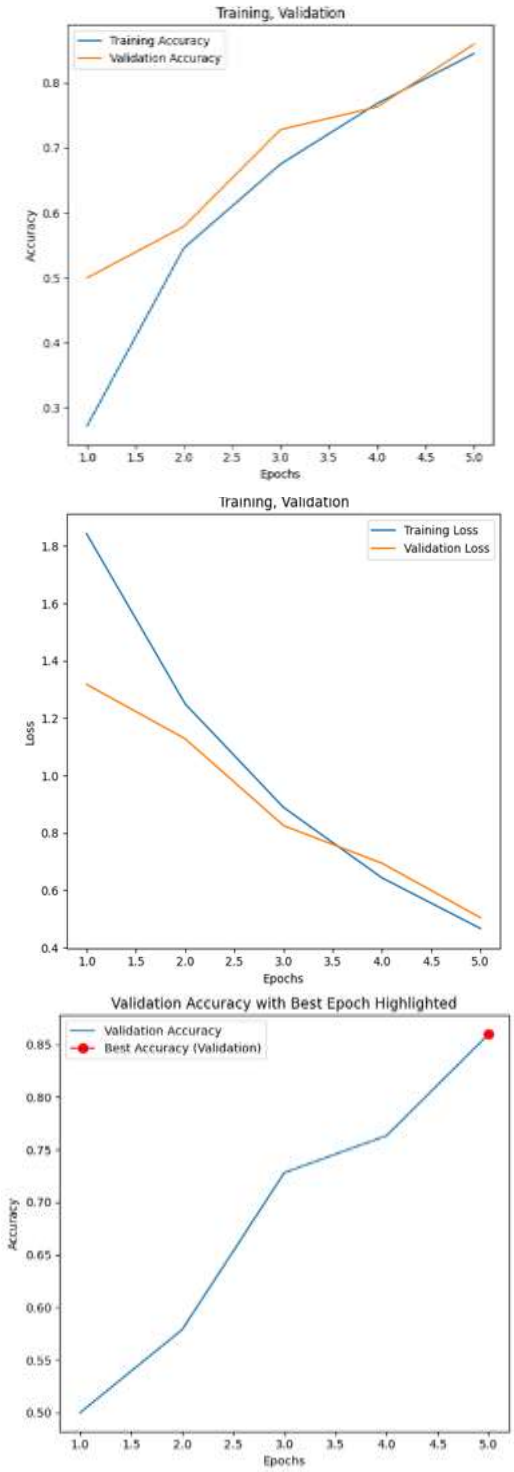

Figure 9. Performance on best fold classic HuBert-noaugmentation (graphic representation)

Analyzing the figure 10, it is noted that the graph highlights a perfect performance of the prediction model for the „happy" and „angry" categories, with all 16 predictions being correct, without any errors in identifying these two emotions.

This precision suggests that the model is excellently calibrated to detect and differentiate be-tween facial expressions or other features associated with these emotional states. This indicates a profound understanding of the distinctive characteristics of „happiness" and "anger" from the dataset used for training. Comparing fig. 3 with fig. 10, it is evident that Hubert LSTM achieved a perfect classification rate of 16 out of 16 instances for the "fearful" and „angry" classes, whereas the Hubert-noaugmentation model achieved a similar flawless performance of 16 out of 16 instances for the „happy" and „angry" classes. This demonstrates the robustness and efficacy of both models in accurately categorizing emotional states, highlighting their proficiency in handling diverse emotional expressions.

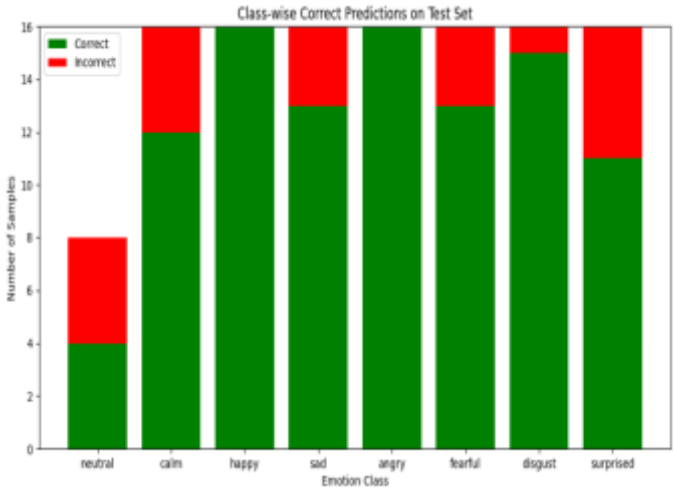

Fig.10. Predictions on best fold Hubert-noaugumentation

The detailed analysis of the confusion matrix results, as depicted in the figure 11, highlights a diverse range of performances in identifying different emotions. These data were obtained from the confusion matrix of the classical Hubert model without augmentation. Positive emotions such as calmness and happiness exhibited precision and recall values above 0.75, suggesting the model's effectiveness in detecting these positive states.

Particularly, happiness achieved the highest scores, with precision, recall, and F1 score all at 0.941, indicating excellent performance in identifying this emotion. On the other hand, negative emotions like sadness, anger, and fear generally achieved good scores but with some variations.

For instance, while sadness showed a precision of 0.65 and recall of 0.867, anger attained a precision of 0.889 and a recall of 0.842. Conversely, fear attained a precision of 0.789, a recall of 0.938, and an F1 score of 0.857,

suggesting the model's high efficiency in identifying this negative emotion. More complex or less frequent emotions such as disgust and surprise demonstrated varied performances.

For example, disgust achieved a perfect precision of 1.0 but a lower recall of 0.647, indicating high precision but potential misses in some cases. Conversely, surprise achieved a precision of 1.0, a recall of 0.917, and an F1 score of 0.957, highlighting the model's efficiency in identifying this emotion despite slightly lower recall. In conclusion, the model exhibits overall good performance in emotion recognition, with an emphasis on positive results and variations in identifying negative or less frequent emotions, suggesting the need for further adjustments to improve performance.

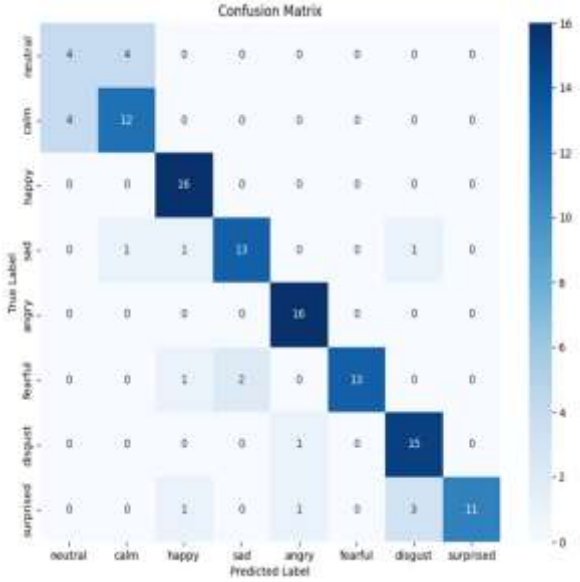

Fig.11. Confusion Matrix HuBert-noaugmentation on best fold

A comprehensive comparison of HuBert-LSTM, HuBert-augmentation, and HuBert-noaugmentation models reveals distinct differences in their performance across various metrics. HuBert-LSTM demonstrates superior precision compared to both HuBert-augmentation and HuBert-noaugmentation models across several emotions, such as Neutral, Calm, and Happy. The precision rates for HuBert-LSTM are consistently higher, suggesting its effectiveness in accurately classifying these emotions.

How-ever, when it comes to recall rates, HuBert-augmentation and HuBert-noaugmentation models exhibit strengths in capturing specific emotions like Sad, Fearful, and Disgust, achieving higher recall rates compared to HuBert-LSTM in these cases. In terms of overall performance, HuBert-LSTM appears to strike a balance between precision and recall, providing a more robust classification of emotions. On the other hand, while HuBert-augmentation and HuBert-noaugmentation models may excel in capturing certain emotions with higher recall rates, they may sacrifice precision in the process. Ad-ditionally, when evaluating emotions such as Angry, Fearful, Disgust, and Surprised, all three models demonstrate strong performances, with precision ranging from moderate to high. However, there are nuanced differences in their capabilities, with each model showing strengths and weaknesses across different emotions.

While HuBert-LSTM, HuBert-augmentation, and HuBert-noaugmentation models each offer unique advantages, HuBert-LSTM stands out as providing a balanced approach to emotion classification, with strong precision across various emotions. Nonetheless, the choice of model ultimately depends on specific requirements and trade-offs between precision and recall in different emotion recognition tasks.

9. Conclusion

The integration of HuBERT with LSTM into a hybrid model for speech emotion recognition (SER) represents a significant advancement in the field of human-computer interaction. This hybrid model capitalizes on the strengths of both architectures, combining HuBERT's proficiency in extracting se-mantic features from speech with LSTM's capability to understand and model the temporal dynamics inherent in audio sequences. The utilization of the RAVDESS dataset has underscored the model's robustness and versatility, enabling it to perform well across a wide spectrum of emotional expressions and intensity levels. The reported results indicate that the HuBert-LSTM model not only surpasses the performance of traditional models but also demonstrates considerable improvements over models using either HuBERT or LSTM in isolation. With a maximum accuracy of 89.1%, the hybrid model shows a promising direction towards enhancing the accuracy and efficiency of emotion recognition systems. This level of performance is particularly noteworthy given the complexity and variability of human emotional expression in speech, highlighting the model's ability to generalize across differ-ent speakers and emotional states. Moreover, the hybrid model's superior performance in handling a diverse range of emotions, including those that are typically challenging for SER systems, such as neutrality and surprise, points to its advanced capability in capturing the nuances of emotional expression. The detailed analysis of precision, recall, and F1 scores across different emotions further confirms the model's efficacy, showcasing its balanced approach to emotion classification. The success testing sets is a testament to its generalization ability and robustness. These qualities make it a highly effective tool for various real-world applications, from enhancing user experience in voice-assisted technologies to supporting mental health assessments through emotional analysis.

In conclusion, the HuBert-LSTM hybrid model represents a significant leap forward in the domain of speech emotion recognition, offering a powerful, efficient, and versatile tool for enhancing human-machine interactions. Its successful application to the RAVDESS dataset highlights its potential for broader implementation, promising to

contribute significantly to advancements in affective computing and beyond. Continued research and refinement of this model could further unlock its capabilities, paving the way for more intuitive and empathetic computer systems. For those interested in my research, I have added a footnote containing a link[2] to the code for all three models, as well as a code testing the Hubert-LSTM model on unlabeled data.

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The author has no conflict of interest to declare that is relevant to the content of this article.