Exploring Emotional Prosody in Tamil: A Study on Speech-Based Emotion Recognition in the Tamil Language

Karthik Raja B[1], Karthikeyan M[1], Nalin M R[1], Pragadishwaran K[1], and Jyothish Lal G[1]

Center for Computational Engineering and Networking, Amrita Vishwa Vidhyapeetham, Coimbatore, India.
g_jyothishlal@cb.amrita.edu

Abstract. This research paper presents a study on emotion recognition in Tamil speech using transfer learning. We employ the Whisper Base model for speech-to-text transcription and develop a customized emotion recognition model for analyzing the transcribed text. The research focuses on training and fine-tuning the models using a large corpus of Tamil speech data. The results demonstrate the effectiveness of the approach in capturing emotions in Tamil speech, with potential applications in sentiment analysis, speech recognition, and emotional AI. This study contributes to the field of Tamil speech analysis and showcases the transferability of models to the Tamil language.

Keywords: Emotion Recognition · Tamil · Transfer Learning · Automatic Speech Recognition

1 Introduction

Emotion recognition, is an emerging field that aims to understand and analyze the emotional content embedded within human communication, such as speech, text, or facial expressions. It plays a crucial role in various applications, including human-computer interaction, virtual assistants, sentiment analysis, and mental health assessment. Accurate emotion recognition enables systems to respond appropriately to user emotions, enhancing the overall user experience.

In recent years, significant advancements have been made in the field of emotion recognition, primarily driven by the rapid development of deep learning techniques and the availability of large-scale data-sets. These techniques allow for the extraction of meaningful patterns and features from complex data, facilitating the identification and classification of emotions with remarkable accuracy.

One of the key challenges in emotion recognition lies in effectively analyzing speech, a rich and dynamic medium of human expression. Analyzing emotions from speech poses unique difficulties due to the variability in cultural influences, individual differences, and language-specific characteristics.

To address these challenges, recent research has explored the application of transfer learning techniques, which leverage pre-trained models from related domains to improve performance in a target domain. Transfer learning has demonstrated great potential in various natural language processing tasks, such as machine translation, sentiment analysis, and speech recognition. By utilizing pre-trained models, researchers can benefit from the knowledge and representations learned from large-scale data-sets and adapt them to specific tasks with smaller data-sets, thus overcoming limitations posed by data scarcity.

In the context of emotion recognition in Tamil speech, the main challenge will be data scarcity. Tamil, a Dravidian language predominantly spoken in Southern part India and Sri Lanka, poses unique challenges in emotion recognition due to its phonetic complexity and linguistic nuances. While there have been previous studies on emotion recognition in other languages, such as English, Spanish, and Mandarin, there is a scarcity of research specifically focusing on emotion recognition in Tamil speech. For many languages there is no available speech data for emotion recognition. We overcome this obstacle by transcribing the speech into text and then analyzing the emotion upon the transcribed text. Specifically, we employ the Whisper Base model, which has been fine-tuned with the Mozilla Wiki-Tamil data-set, for speech-to-text transcription. Whisper Base, a state-of-the-art model, leverages deep learning techniques to capture the acoustic features of spoken language, providing accurate transcriptions of Tamil speech.

Furthermore, we develop a customized emotion recognition model specifically tailored for analyzing the transcribed Tamil text. This model is trained and fine-tuned using a large corpus of labelled Tamil emotion-text data, enabling it to capture the nuances and subtleties of emotions expressed in the written form of the Tamil language.

The effectiveness of our approach is demonstrated through extensive experiments and evaluations. By leveraging the enhanced capabilities of the Whisper Base model, along with the fine-tuning process using the Mozilla Wiki data-set, we achieve improved accuracy in transcribing the Tamil speech. The results of our study have implications for sentiment analysis, speech recognition, and emotional AI, showcasing the potential for applying text-based emotion recognition in various real-world scenarios.

Moreover, this research project also explores the transferability of models from other languages to Tamil, shedding light on the generalizability of emotion recognition models and their adaptability to different linguistic contexts. The findings of this study will pave the way for further advancements in the analysis of emotional speech in Tamil and open up avenues for improved human-computer interaction and natural language processing systems.

2 Literature Review

There have been various approaches researched for Emotion Recognition on text such as Keyword-based approaches, Rule-based approaches, deep learning approaches.

Keyword-based approach Keyword based approach is the most basic approach out of all. Keyword approach as the name suggests, classifies the text based on presence of particular keywords that indicate certain emotions. Example "Her laughter echoed through the room, spreading infectious joy to everyone around.", here the word “laughter” indicates that the sentence expresses emotion of happiness and joy. [1,22] investigates the Keyword based approach for emotion recognition. Perikos and Hatzilygeroudis [22] utilized NLP techniques, including POS tagging and parsing, to analyze the structure of a sentence. The emotion words were recognized using WordNet-Affect. Shivhare et al. [21] proposed a model that used an ontology with the keyword-spotting technique.

Rule-based approach The rule-based approach to interpreting information involves using knowledge manipulation techniques to make sense of data. First, the emotion data-set is prepared by performing text preprocessing tasks like breaking the text into tokens, removing unnecessary words, determining word forms, and understanding the grammatical structure. subsequently, emotion rules are extracted using a combination of linguistic, statistical, and computational methods. The most relevant and effective rules are selected for further analysis. Finally, these rules are applied to the emotion data-set, helping to determine the appropriate labels for each emotion. Lee et al. [20] proposed a rule-based model for recognizing cause events that evoke emotions in Chinese. They constructed an annotated emotion corpus and calculated the distribution of cause event types, positional information, and keywords for each emotion class. By identifying linguistic cues and developing linguistic rules, they built a system that effectively recognized the causes of emotions. Experimental results demonstrated its promising performance in cause occurrence and event recognition.

Classical learning-based approach A classical learning-based approach provides systems the ability to automatically learn and improve from experience. Classical learning-based approaches involves using Machine Learning Algorithms for the classification tasks. As per our review on other works in this task of Emotion Recognition, SVM was the most used Machine Learning Algorithm used. Table 1 lists few of the previous works done based on this approach.

SNo	Author	Work
1	Danisman and Alpkocak [5]	proposed a vector space model (VSM), where each class of emotion is represented by a set of documents.
2	Ghazi et al. [3]	proposed a novel hierarchical approach to emotion recognition
3	Xu et al. [7]	proposed a hierarchical emotion classification for a Chinese microblog.
4	Zhang et al. [8]	proposed a knowledge-based topic model (KTM) to identify implicit emotion features. Additionally, a hierarchical emotion structure was employed to classify emotions into 19 classes of four levels using an SVM.
5	Kim et al. [2]	presented an evaluation of the categorical model and the dimensional model.
6	Thomas et al. [9]	investigated the use of multinomial naïve Bayes (MNB) with unigram, bigram, and trigram features from English text.

Table 1: List of works on classical learning-based approaches used in emotion classification.

Deep learning-based approach The Deep Learning-based approach, involves using Artificial Neural Network and different architectures of the same for the task of emotion recognition. LSTM is the most commonly used model for this task. Table 2 lists the works proposed based on Deep learning-based approach.

Another important aspect of emotion recognition is the emotion modelling task. Emotional modelling refers to the process of representing and understanding human emotions in a structured or computational manner. Psychology based research has distinguished three major approaches for emotion modelling [17,18]. Three dominant modelling approaches are :

Categorical approach, Dimensional approach, Appraisal-based approach.

- The **categorical approach** proposes that there exists a small set of basic emotions that are universally recognized and understood. These core emotions, including happiness, sadness, anger, fear, surprise, and disgust, are considered fundamental to human experiences across different cultures and backgrounds.
- In contrast, the **dimensional approach** takes a broader perspective on emotions. It suggests that emotional states are not isolated entities but rather interconnected and can be described through three dimensions: valence, arousal, and power.
  - Valence refers to the positive or negative nature of an emotion. It captures whether an emotion is experienced as pleasant or unpleasant. For

SNo	Author	Work
1	Wang et al. [12]	utilized a convolutional neural network (CNN) to solve multi-label emotion recognition.
2	Baziotis et al. [13]	proposed a deep learning model for multi-label emotion recognition English in tweets. Their model consisted of a two-layer bidirectional long short-term memory (Bi-LSTM) equipped with multi-layer self-attention mechanism.
3	Meisheri and Dey [11]	Two parallel architectures were designed to generate the representation using various pretrained embeddings, the resulted matrix was fed into a Bi-LSTM.
4	Du and Nie [4]	proposed a deep learning model that uses pretrained word embeddings for the tweets representation. The embeddings were fed into a gated recurrent unit (GRU), and the classification was obtained using a dense neural network (DNN).
5	Xiao [10]	They fine-tuned the following models: the universal language model (ULM), BERT model, OpenAI's Generative Pretraining (GPT) model, DeepMoji model. The results show that the ULM model has the best performance among the other models.
6	Basile et al. [6] Ma et al. [14] Ge et al. [15] Ragheb et al. [16]	These Four works propose deep learning models for emotion recognition in textual conversation. All the works uses Bi-LSTM with ANN layers. But each work used different data-set and different preprocessing methods and representation of data.

Table 2: List of works proposed based on Deep learning-based approach.

example, happiness is associated with positive valence, while sadness is linked to negative valence.

- Arousal reflects the level of activation or energy associated with an emotion. It ranges from low arousal, which corresponds to feelings of calmness and relaxation, to high arousal, which represents intense excitement or agitation.
- Power represents the intensity or strength of an emotion. It signifies the degree to which an emotion is felt, ranging from subtle or mild to overwhelming or profound.

– The **appraisal-based approach** builds upon the dimensional view by incorporating appraisal theory. According to this perspective, emotions arise from the evaluation and interpretation of events based on an individual's personal experiences, goals, and opportunities for action. This approach acknowledges that emotions encompass various significant components, including cognition, physiology, motivation, reactions, feelings, and expressions.

By considering these different approaches, we gain a deeper understanding of the complexity and diversity of human emotions. Table 1 gives summary of the three approaches.

3 Data Description

In our study, we have utilized two different data-sets. First data-set is the Mozilla Common Voice project data-set for Tamil. First data-set was used for fine-tuning the Whisper Base model for Tamil speech transcription. Second data-set is the Tamil emotional tweet data. Second data-set was used training our emotion recognition model.

The first data-set used in this study is obtained from the Mozilla Common Voice project, an open-source initiative that aims to gather and share voice data for machine learning research (https://commonvoice.mozilla.org/en/data-sets). The data-set contains speech and its corresponding transcription for Tamil and Malayalam. The training data consists of 391 hours of speech from 850 Tamil voices along with their respective transcriptions with makes over 4,000 data samples. The audio are recorded by different actors for different voice. Captured at a sampling rate of 48,000 Hz and a bit rate of 64,000 bps, ensuring high-fidelity recordings that are ideal for speech recognition tasks.

The second data-set we utilized focuses on emotional analysis of Tamil tweets collected from the social media platform Twitter. It consists of 19,500 data points and aims to classify tweets into emotional categories, including sadness, joy, surprise, love, fear, and anger.The data-set was split into train, test and validation data, each consisting of 16,000, 2,000, and 1,500 data points respectively. To ensure data quality, the data-set underwent preprocessing steps such as language normalization and duplicate removal.

During the annotation process, emotion labels were assigned to each tweet using guidelines and quality control measures. This ensures consistency in labeling and enhances the overall quality of the data-set.

The following points explore the data-set's characteristics, including its size, text length distribution, word frequencies, and emotion label percentages. These visualizations and data manipulations help us gain a deeper understanding of the data-set and inform subsequent analysis and modeling decisions.

- Data-Frame Size contains 16,000 samples and 2 columns. This information helps us understand the data-set's structure and dimensions.
- Duplicate Entries initially, there are 1,097 duplicate entries present in the data-set. However, these duplicates are then removed, resulting in a data-set with no duplicate entries. This step ensures the integrity and quality of the data.
- Length of Text Distribution considered by a histogram with a box plot representation is created to helps us understand the distribution of text lengths

in the data, providing insights into the variability and characteristics of the text data. Refer Fig 2.

– A pie chart is created to show the percentage distribution of each emotion category: joy (33 %), surprise (4%), love (8%), fear (12%), anger (13%), and sadness (29%). These visualizations offer an overview of the distribution and balance of emotions in the training set. Refer Fig 1

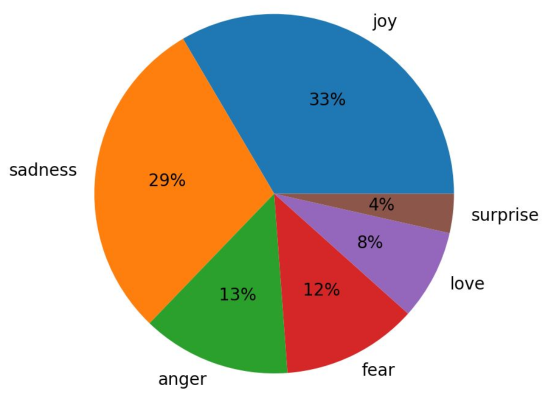

Fig. 1. Pie chart representation of Emotion label distribution

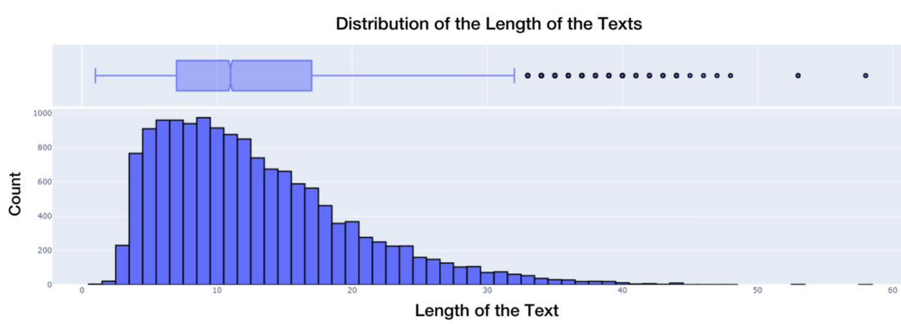

Fig. 2. Histogram representation of Distribution of the length of the texts

4 Proposed Methodology

In our proposed methodology, we utilise Whisper base model, which acts as a robust and comprehensive tool for voice recognition tasks trained on a large and diverse audio data-set which has the capacity to do multilingual speech recognition, speech translation, and language identification and has 74 M parameters. This multitasking approach is built on the Transformer sequence-to-sequence architecture, which allows it to replace many stages of a standard speech-processing pipeline.

Initial part of the methodology is whisper-based modelling, the whisper Base model is fine-tuned with large corpus of Tamil Speech data which is critical in enhancing the accuracy of transcriptions for Tamil speech. This model accepts the speech as input (in our example, Tamil speech files) and returns the transcribed text for it. We improve the quality of transcribed data by utilising whisper-based modelling, guaranteeing that the emotional nuances of Tamil speech are successfully recorded and kept for subsequent analysis.

Next, our methodology incorporates a powerful Long Short-Term Memory (LSTM) architecture, designed to capture the intricate temporal dynamics and contextual information embedded within Tamil speech's emotional content. LSTMs, a type of recurrent neural network, excel in modeling sequential data and are particularly well-suited for tasks like speech recognition and sentiment analysis.

The LSTM architecture in our methodology serves as a dynamic framework for extracting meaningful features and patterns from preprocessed Tamil speech data. It consists of several layers, each with a specific function (refer Figure 3 and 4):

- **Embedding Layer:** This initial layer converts the input Tamil speech data into a dense vector representation, facilitating the extraction of essential features that capture the emotional nuances of the speech.
- **Bidirectional LSTM Layer:** By employing bidirectional LSTMs, our model considers both past and future context while analyzing the speech data. This enables the architecture to capture the intricate dependencies and temporal dynamics inherent in the emotional content of Tamil speech.
- **Flatten Layer:** The flatten layer reshapes the output of the bidirectional LSTM layer into a one-dimensional tensor, preparing it for subsequent dense layers.
- **Dense Layers:** These layers perform high-level feature extraction and non-linear transformations, allowing the model to learn complex patterns and representations associated with accurate emotion recognition.
- **Dropout Layer:** To mitigate overfitting and enhance generalization, we incorporate dropout regularization within the LSTM architecture. By randomly deactivating a fraction of neurons during training, the model learns to rely on the remaining neurons, promoting robustness and preventing the overemphasis of specific features.
- **Output Layer:** The final dense layer produces emotion classification results for the input Tamil speech, mapping the extracted features to specific emotion categories.

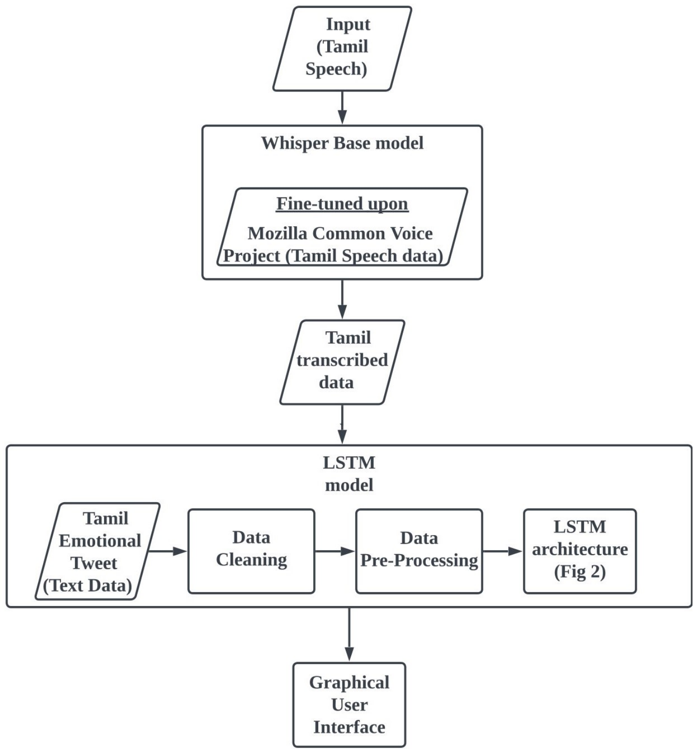

Fig. 3. Proposed Methodology for the Model.

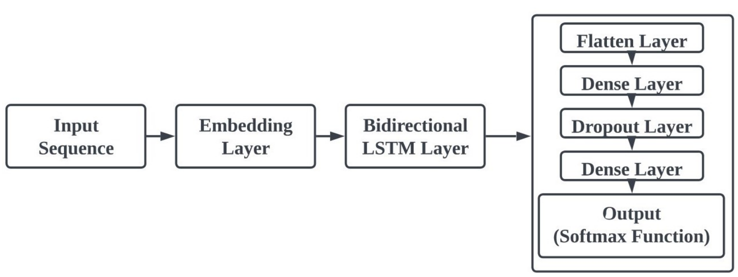

Fig. 4. LSTM architecture used for emotion recognition model.

To ensure accessibility and ease of use, we integrate the trained LSTM model with a graphical user interface (GUI). This user-friendly platform allows individuals to input their Tamil speech, and the system processes it using the trained model, providing real-time emotion recognition results. This integration empowers users to interact effortlessly with the system, gaining immediate insights into the emotions conveyed within their speech.

By incorporating the LSTM architecture and GUI integration, our methodology establishes a robust and user-friendly emotion recognition system for Tamil speech. It captures the intricate temporal dynamics, contextual information, and emotional nuances, enabling accurate emotion classification and fostering a deeper understanding of the spoken emotions.

4.1 Performance Metrics

1. **Word Error Rate** The Word Error Rate measures the accuracy of the transcribed text generated by the speech-to-text transcription system. It quantifies the discrepancy between the original text and the transcribed text in terms of word-level errors. The formula for WER is:

$$WER = \frac{Substitutions + Deletions + Insertions}{TotalWords} \tag{1}$$

2. **Accuracy:** Accuracy measures the overall correctness of the model's predictions. It is calculated as the ratio of correctly classified instances to the total number of instances in the data-set. The formula for accuracy is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

3. **Precision:** Precision measures the proportion of true positive predictions out of all positive predictions made by the model. It provides insights into the model's ability to avoid false positive errors. The formula for precision is:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

4. **Recall:** Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that are correctly identified by the model. It helps assess the model's ability to avoid false negative errors. The formula for recall is:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

5. **F1-Score:** The F1-score is a harmonic mean of precision and recall, providing a balanced measure of the model's performance. It combines precision and recall into a single metric, taking into account both false positives and false negatives. The formula for F1-score is:

$$F1\text{-}score = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \tag{5}$$

5 RESULT AND OBSERVATION

In this section, we present the results of our study on emotion recognition in Tamil speech. We evaluate the performance of our customized emotion recognition model and Fine-tuned Whisper Base model. The evaluation metrics used for evaluating Emotion recognition Model include accuracy, precision, recall, and F1-score. On the other hand Word Error Rate (WER) is used as evaluation metrics for evaluating performance of Transcription model.

5.1 Whisper Base Model

The model was able to perform with very low Word Error Rate of 2% for Tamil speech to text transcription.

5.2 Emotion Recognition Model

The overall accuracy of our customized emotion recognition model was 79%, correctly classifying emotions in Tamil speech. We evaluated the model's performance using various metrics such as precision, recall, and F1-score.

For the specific emotional categories, the model achieved the following scores:

Emotion	Accuracy	Precision	Recall	F1-score	Instances
Sad	83%	85%	82%	84%	480
Joy	84%	86%	84%	85%	551
Love	59%	58%	62%	60%	84
Anger	67%	70%	77%	74%	168
Fear	60%	70%	72%	71%	141
Other	44%	37%	45%	41%	31

The macro-average for precision, recall, and F1-score across all emotional categories was 68%, 70%, and 69%, respectively. The weighted average across all categories yielded precision, recall, and F1-score of 80%, 79%, and 79%, respectively.

During the training process, we monitored the variation of accuracy with respect to epochs. We observed that the accuracy gradually increased with each epoch, reaching a plateau after a certain number of epochs. To visually represent this variation, we have included a graph showing the accuracy curve over the training epochs (refer to Figure 5).

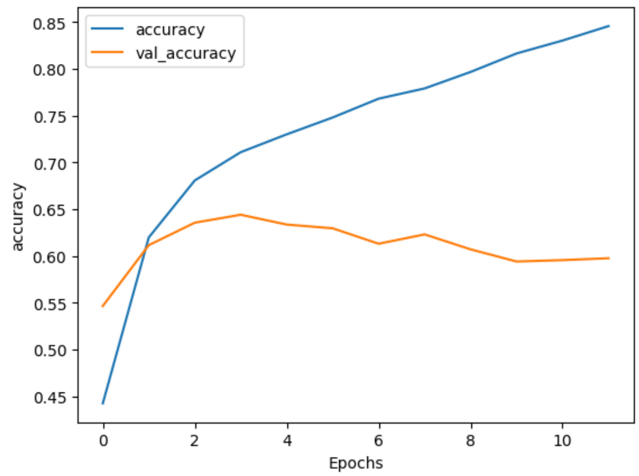

Fig. 5. Accuracy VS Number of epochs plot

6 CONCLUSION

Our study demonstrates the effectiveness of our customized emotion recognition model in capturing emotions in Tamil speech. By leveraging transfer learning techniques and fine-tuning, we achieve accurate speech-to-text transcription using the Whisper Base model. The model, trained on a comprehensive corpus of Tamil speech data, exhibits high accuracy in transcription. Emotion recognition is subsequently performed on the transcribed data, by our model. Through the utilization of consistent regularization, we enhance the accuracy and performance of our emotion recognition model. The model effectively captures the nuances of emotions within the transcribed Tamil text.

While our results showcase promising performance in emotion recognition, further research is needed to optimize the model architecture and improve recall for certain emotional states. This research contributes to the field of sentiment analysis and emotional AI, with applications in sentiment-aware technologies and personalized recommendation systems for Tamil speech.

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