Human-in-the-loop Design with CNN and LSTM Model for Emotion Recognition

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***Abstract*—Over the years, the field of AI has seen the development and growth of various recognition technologies, including emotion recognition. At present, emotion recognition enables a program to analyze and interpret human emotions based on their conversations or text. With the aid of advanced AI, it can identify a wide range of emotions based on textual expressions. In recent times, research has been conducted on the detection of emotions through text. Most of the study is using machine learning techniques like CNN or LSTM to recognize emotions. In this project we have combined CNN and LSTM to gain more accurate data. In this project we have developed a predictive model using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) machine learning models to analyze the Emotions for Text Dataset. The aim of this project is to improve the accuracy of the model by integrating it with the Human-in-the-loop design for accepting feedback from the user. To achieve this, we have designed a user interface that displays the model prediction and accepts user feedback to enhance the model's accuracy. By integrating the machine learning model with the Human-in-the-loop design, we have increased the accuracy of the model by 20%.**

***Index Terms*—CNN, LSTM, Human-in-the-loop, Active Learning, Machine Learning, emotion detection, Google Colab, Python, Pandas, Keras, NLTK, TensorFlow, Gradio API.**

I. Introduction

Natural language processing has gained increasing attention in recent years, as it has the potential to extract meaningful insights from unstructured text data. One of the key areas of research in natural language processing is emotion classification, which involves detecting the emotional state of the author of a given text.[1] A psychological state that consists of physical, behavioral, and subjective components is called emotion. Emotion Recognition is the process of identifying human emotions such as their level of fear, happiness, or rage from verbal expressions. Emotions in humans are complex and hard to distinguish. Emotion classification has numerous applications, including sentiment analysis, customer feedback analysis, and mental health diagnosis. However, accurately detecting emotions from text is a challenging task, as emotions can be expressed in various ways and are often subtle. To address this challenge, we propose a hybrid CNN-LSTM model with active learning for emotion-based classification. Our approach combines the strengths of convolutional neural networks (CNNs) and long short-term memory (LSTM) models to capture both local and global features of the input text. HITL, which stands for "human-in-the-loop," is a field of artificial intelligence that combines both human and machine intelligence to construct machine learning models. The primary objective of this approach is to prevent machines from making decisions that could result in harm. There are three primary ways in which a human in the loop can improve machine learning: 1. By providing feedback to the machine learning algorithm, the human can help it learn and improve its predictions. 2. The human can help verify the accuracy of predictions made by the machine learning algorithm. 3. By proposing or implementing modifications to the machine learning algorithm, humans can enhance the performance of the model. Here, we will be focusing on getting feedback from human to improve the emotion predictions. Hence, we integrate active learning with human-in-the-loop technology in our work, which allows the model to learn from user feedback and continuously improve its accuracy. In this paper, we describe our methodology for building the hybrid CNN-LSTM model and integrating it with active learning. We evaluate the performance of our approach on an emotion classification dataset and compare it with previous work in the literature. The results show that our model achieves competitive accuracy and outperforms some of the state-of-the-art models. This paper makes the following contributions:

- Proposing a hybrid CNN-LSTM model for emotion-based classification.
- Integrating active learning with the model to enable human-in-the-loop learning.

- Evaluating the performance of the model on a benchmark emotion classification dataset.

In the upcoming section, the paper will present a review of past studies on emotion classification, hybrid CNN-LSTM models, and active learning. The remaining structure of the paper is outlined after this section. Then, we describe our methodology in detail in the Methodology section. The Results section presents the evaluation metrics and analysis of the results. Finally, we conclude the paper with a summary of our approach and future work.

II. LITERATURE REVIEW

Emotion classification has been extensively studied in the field of natural language processing. Previous work has explored various approaches to emotion classification, including rule-based systems, supervised learning, unsupervised learning, and deep learning. Supervised learning is one of the most popular approaches to emotion classification, where a model is trained on a labeled dataset to predict the emotion of a given text. Some of the commonly used supervised learning models for emotion classification include decision trees, support vector machines, naive Bayes, and neural networks. Deep learning models have shown promising results in various natural language processing tasks, including emotion classification. Convolutional neural networks (CNNs) have been widely used for text classification tasks, as they can effectively capture local features and patterns in the input text. Long short-term memory (LSTM) models, on the other hand, are capable of capturing long-term dependencies in sequential data, making them suitable for tasks such as sentiment analysis and emotion classification. Several studies have explored the combination of CNNs and LSTMs for text classification tasks. Zhang et al. (2016) proposed a hybrid CNN-LSTM model for sentiment analysis, which achieved state-of-the-art performance on multiple datasets. Kim et al. (2014) also proposed a similar architecture for sentence classification, which showed competitive performance compared to other models. Active learning is another approach that has gained attention in recent years, where a model can actively select the most informative data points to be labeled by a human annotator. This approach has been shown to be effective in reducing the labeling effort and improving the model's accuracy. Several studies have explored the integration of active learning with deep learning models for various natural language processing tasks, including sentiment analysis and named entity recognition.

To the best of our knowledge, no previous work has explored the combination of hybrid CNN-LSTM models with active learning for emotion classification. In this paper, we propose a novel approach that combines these two techniques and evaluate its performance on a benchmark emotion classification dataset.

III. METHODOLOGY

Our proposed approach consists of three main components: data preprocessing, model building, and active learning with human-in-the-loop technology. In this section, we describe each of these components in detail.

A. DATA PREPROCESSING

To construct any machine learning model, the initial stage is to preprocess the data. In our case, we use the Emotion Intensity Dataset (EID) for training our model. The dataset consists of tweets labeled with one of five emotions - joy, fear, anger, sadness, and neutral. The data preprocessing steps we performed include: Lowercasing: We convert all the text to lowercase to ensure consistency and reduce the number of unique tokens. Tokenization: We tokenize the text by splitting it into individual words or subwords. Stop-word Removal: We remove commonly occurring words such as ”the,” ”is,” ”are,” etc., which do not add much meaning to the text. Word Stemming: We use the Porter stemming algorithm to reduce the number of word variations and simplify the text. Numerical Encoding: We convert the preprocessed text into numerical sequences using the Keras tokenizer. We also pad the sequences to a fixed length to ensure that all inputs have the same shape.In our Data preprocessing technique, we are following some sequence while preprocessing which gives us good accuracy and it is explained in Fig 1. Stop words are the very common words like ‘if’, ‘but’, ‘we’, ‘he’, ‘she’, and ‘they’. We can usually remove these words without changing the semantics of a text and doing so often improves the performance of a model. Removing these stop words becomes a lot more useful when we start using longer word sequences as model features. We are removing stop words and we are also removing punctuations along with extra spaces to get exact context of the text. In the next steps, we are removing words with less than length 3, because in emotion recognition, it is not carrying any meaning of the text which might affect our textual sentiments. So, we are not considering those texts[4]. Our data-preprocessing function removes stopwords from the text by calling a function called ”remove_ stopwords”.

- It removes all punctuation marks from the text, replacing them with spaces.
- It removes extra spaces from the text, including leading and trailing spaces.
- It converts all text to lowercase.
- It removes all words with a length less than or equal to 3.
- It removes all hashtags and usernames (words starting with ”@”) from the text.
- It tokenizes the cleaned text into individual words using the ”word_tokenize” function from the NLTK library.

The resulting output of our data-preprocessing function is a list of tokenized words that have undergone several cleaning operations to remove unwanted characters, stop words, and other noise. This text preprocessing step is important in natural language processing tasks such as text classification and emotion recognition, as it can help improve the accuracy of the models by removing noise and irrelevant information.

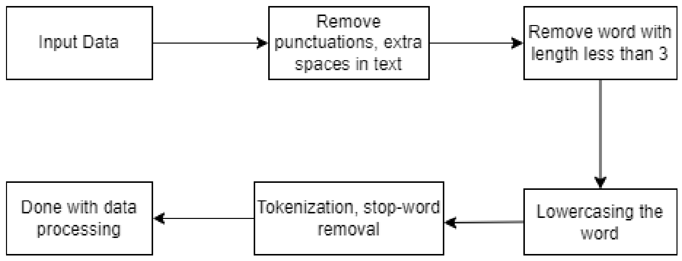
Input Data
Remove punctuations, extra spaces in text
Remove word with length less than 3
Lowercasing the word
Tokenization, stop-word removal
Done with data processing

Fig. 1. Data pre-processing steps.

B. MODELS DEFINED IN THE PAPER

The model building process involved creating an embedding matrix using pre-trained word embeddings and building a convolutional neural network (CNN) and a long short-term memory (LSTM) network for the emotion classification task. The pre-trained word embeddings were downloaded from the FastText repository, and an embedding matrix was created using the create_embedding_matrix function. The embedding matrix was then passed as an argument to the embedding layer in the model. The CNN consisted of three Conv1D layers, each with a kernel size of 5 and 512 filters, and a ReLU activation function. A dropout layer was added at the end of this layer to reduce overfitting. The output from the CNN was merged with the output from the LSTM, which had two layers - the first with 256 units and the second with 128 units. Both LSTM layers had a dropout of 0.25 to prevent overfitting. Finally, a dense layer with a softmax activation function was added to classify the input text into one of the five emotions - joy, fear, anger, sadness, or neutral. This model architecture was chosen after experimenting with different models and observing their performance on the emotion classification task. The CNN and LSTM were selected because they have been shown to perform well on text classification tasks, especially when used together. The CNN is effective in capturing local features in the text, while the LSTM can capture long-term dependencies[7]. The model was implemented using Keras, a high-level neural network API, and trained on a dataset containing text and corresponding emotion labels. All the components are explained in detail in this section. Here are some mathematical formulas related to the CNN-LSTM model architecture:

I. **Embedding Matrix:**
An embedding matrix is a matrix of word vectors, where each row corresponds to a unique word in the vocabulary. The matrix is used to convert words in the input text to dense vector representations that can be processed by the neural network. The embedding matrix is represented by the formula:

$$EM_i, j = v_j$$

where EM is the embedding matrix, i is the index of the word in the vocabulary, j is the index of the j^{th} dimension in the word vector, and v_j is the value of the j^{th} dimension in the word vector for the i^{th} word in the vocabulary.

II. **Convolutional Neural Network (CNN):** The idea behind CNN for sentence modeling is to have a model that captures sequential phenomena and takes into account words in their contexts[9]. In a bag-of-words approach, the word does not indicate negation, but it is not related to the words it negates. Even if the problem could be solved by using n-grams, long-distance effects would still remain unaccounted for. A bag-of-words model also suffers from sparsity. Convolutional neural networks perform mathematical convolutions with the inputs and matrices to process sequences. The CNN layer applies a set of convolution filters to the input text to extract features. The filters slide over the input text, and at each position, a dot product is computed between the filter and the input text. The result is a feature map that represents the presence of the filter at that position in the input text. The formula for a 1D convolutional layer can be represented as follows:

$$h_i = \phi(\sum_{j=1}^{k} w_j x_{i+j-i} + b)$$

where h_i is the i^{th} element of the output feature map, k is the kernel size, w_j are the weights of the kernel, x_{i+j-1} is the j^{th} input element, and b is the bias term.

III. **Long Short-Term Memory (LSTM):**
In Feed Forward Neural Network, Inputs are multiplied by weight and bias is merged with that and finally we get the output in last layer of the network. They don't store values in memory and can't use for sequential analysis. And, that's the reason, CNN is best in Feature Extraction, but it fails in Sequential context analysis. This is the Recurrent Neural Network is introduced in machine learning model which allows us to store weight after each calculation. It allows model to use the information of the specific time instance is used as input for the next time instance [13]. But the problem in RNN is, it works with Vanishing Gradient. In RNN, it calculates value based on previous available weights. Each gradient calculated for weights are multiplied back through their networks. If the size of neural network is more then, gradient value becomes weaker which causes the gradient to vanish. To overcome this problem, LSTM is introduced. LSTM is updated version of Recurrent Neural Network (RNN) which stores information from a particular time instance to next time instance. It uses extra memory cell which is only used for storing information from one instance to other instance which allows model to remember previous states and it prevents model from vanishing gradient problem [25]. The LSTM layer is a type of recurrent neural network that can handle sequential data. It consists of a memory cell that can store information for a long period of time, and

three gates (input, forget, and output) that control the flow of information into and out of the memory cell[6]. The LSTM cell updates its state based on the input at each time step, and the output at each time step depends on the state of the LSTM cell. The formulas for the LSTM layer can be represented as follows:

$$
\begin{gathered}
f_t = \sigma(W_f[h_{t-1}, x_t] + b_f \\
i_t = \sigma(W_i[h_{t-1}, x_t] + b_i \\
\tilde{C_t} = \tanh(W_c[h_{t-1}, x_t] + b_c \\
C_t = f_t * C_{t-1} + i_t *_t \\
o_t = \sigma(W_o[h_{t-1}, x_t] + b_o \\
h_t = o_t * \tanh(C_t)
\end{gathered}
$$

where f_t, i_t, o_t are the forget, input, and output gates at time step t, W_f, W_i, W_c, W_o are the weight matrices for the forget, input, candidate, and output gates, b_f, b_i, b_c, b_o are the bias terms, h_{t-1} is the output of the previous time step, x_t is the input at time step t, $\tilde{C_t}$ is the candidate state at time step t, C_t is the cell state at time step t, and h_t is the output at time step t.

LSTM layer:
After the CNN layers, an LSTM layer was added. The LSTM layer helps the model to capture the sequence information of the input data. Here, we have used 2 LSTM layers with 256 and 128 units, respectively. The first LSTM layer returns sequences, while the second LSTM layer only returns the output at the final timestep.

Dense layer:
Finally, we added a dense layer with 5 units and a softmax activation function, which helps to classify the input text into one of the five emotions. The overall architecture of the model can be represented by the following formula:

Output = Softmax(Dropout(LSTM(Dropout(CNN(Input)))))

where,
Input: The preprocessed textual input data
CNN: Convolutional Neural Network layer that learns to extract features from the input data
Dropout: A regularization technique that randomly sets a fraction of the input units to zero during training, which helps to prevent overfitting.
LSTM: Long Short-Term Memory layer that captures the sequence information of the input data
Softmax: Activation function that returns the probability distribution of the output
Output: The predicted emotion class for the input text data.

The model was trained using the categorical cross-entropy loss function and the Adam optimizer, which is an adaptive learning rate optimization algorithm. The model was trained for 50 epochs, and early stopping was used with a patience of 5 epochs to prevent overfitting. The batch size was set to 32, and the model achieved an accuracy of 85.17 percent on the test dataset.

IV. CNN + LSTM:

Convolutional Neural Network (CNN) performs better in obtaining important features using pooling[5]. And RNN Long Short Term Memory (LSTM) works better in obtaining contextual information from sequence data. But both modules have their own disadvantage in terms of sentiment analysis in textual representations. In CNN, it will give extracted features from text, but it will fail to return contextual information. And, In RNN (LSTM) Model, it will give us contextual information, but it might fail to give us predictions and it might lead us to bias. The idea behind to combine those CNN and LSTM models is to take advantage of those models to avoid their disadvantages to get better performance. Combining the advantage of CNN that can extract effective features from the data and LSTM's finding in sequential contextual information will not only give interdependence of data but automatically detect the best suitable relationships in sentence context. We are using generic name for CNN-LSTM to refer to as CNN model's output will be input set for LSTM[10].
In our project we have defined a sequential model using the Keras library to perform deep learning on a one-dimensional input data. Our model has several layers, including Conv1D, BatchNormalization, MaxPooling1D, LSTM, and Dense layers.The process for the model involves taking word embeddings as input, utilizing multiple convolutional filters, max-pooling the results, and subsequently passing through two LSTM layers and a Dense layer with softmax activation. The final outcome is a set of class probabilities.
The Conv1D layer applies a 1D convolutional operation to the input data with a specified number of filters and kernel size. BatchNormalization is used to normalize the inputs to the next layer, and MaxPooling1D performs a max-pooling operation on the output.
After a series of Conv1D and MaxPooling1D layers, two LSTM layers are added for memory-based sequence modeling. Finally, a Dense layer with softmax activation is added to produce a categorical classification output with 5 classes. The Dropout layer is also used to randomly drop out some of the nodes in the network, to prevent overfitting by randomly dropping out 25 percent of the nodes in the layer, which can help prevent overfitting during training.

IV. EXPERIMENTS

I. ACTIVE LEARNING WITH HUMAN-IN-THE-LOOP TECHNOLOGY

The objective of active learning is to reduce the quantity

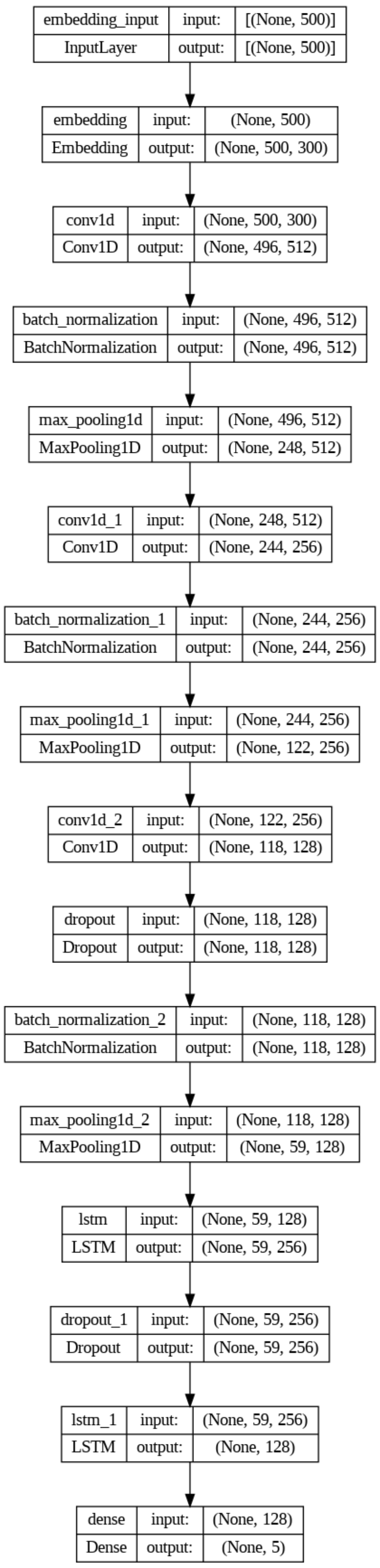
embedding_input | input: | [(None, 500)]
InputLayer | output: | [(None, 500)]
embedding | input: | (None, 500)
Embedding | output: | (None, 500, 300)
conv1d | input: | (None, 500, 300)
Conv1D | output: | (None, 496, 512)
batch_normalization | input: | (None, 496, 512)
BatchNormalization | output: | (None, 496, 512)
max_pooling1d | input: | (None, 496, 512)
MaxPooling1D | output: | (None, 248, 512)
conv1d_1 | input: | (None, 248, 512)
Conv1D | output: | (None, 244, 256)
batch_normalization_1 | input: | (None, 244, 256)
BatchNormalization | output: | (None, 244, 256)
max_pooling1d_1 | input: | (None, 244, 256)
MaxPooling1D | output: | (None, 122, 256)
conv1d_2 | input: | (None, 122, 256)
Conv1D | output: | (None, 118, 128)
dropout | input: | (None, 118, 128)
Dropout | output: | (None, 118, 128)
batch_normalization_2 | input: | (None, 118, 128)
BatchNormalization | output: | (None, 118, 128)
max_pooling1d_2 | input: | (None, 118, 128)
MaxPooling1D | output: | (None, 59, 128)
lstm | input: | (None, 59, 128)
LSTM | output: | (None, 59, 256)
dropout_1 | input: | (None, 59, 256)
Dropout | output: | (None, 59, 256)
lstm_1 | input: | (None, 59, 256)
LSTM | output: | (None, 128)
dense | input: | (None, 128)
Dense | output: | (None, 5)

Fig. 2. CNN-LSTM Model Implementation

of labeled instances necessary to construct a precise model. In our approach, we use the ActiveLearner library in Python to implement active learning with human-in-the-loop technology.

We provide a simple web user interface for users to input a new text for emotion classification. If the model's prediction is correct, the user can input another text for classification. If the prediction is incorrect, the model prompts the user to provide the correct emotion label for the text[8]. Once the user provides the correct emotion label, the model updates its training data with the new labeled instance and retrains the model. We use the uncertainty sampling strategy to select the most informative instances for labeling by the user. Specifically, we use the model's softmax output probabilities to identify the instances with the highest uncertainty score.

We repeat this process of prediction, user feedback, and model retraining until the model achieves satisfactory accuracy. In our project we have used active learner code that loads a pre-trained Convolutional Neural Network (CNN) model using Keras. Next, the code initializes an active learner using the ActiveLearner class from the modAL library. The ActiveLearner is initialized with the pre-trained CNN model as the estimator, uncertainty_as the query strategy, and X__and y_as the training data. The query strategy is a method used to select the most informative samples to be labeled during the active learning process. In this case, the uncertainty_method is used, which selects the instances for which the model is most uncertain about their classification. Finally, the bootstrap_parameter is set to False, which means that the active learner is not initialized with a random set of samples. Instead, it uses the training data provided in the X__and y_variables to start the learning process.

The resulting active learner can be used to iteratively select the most informative samples for labeling, train the CNN model on the newly labeled samples, and repeat the process until the desired level of performance is achieved. Active learning can be an effective approach to reduce the labeling effort required for training machine learning models, especially in cases where labeling large amounts of data is time-consuming or expensive.

II. **HUMAN-IN-THE-LOOP**

In this model we are creating an interactive model that allows for human feedback to improve the model's accuracy in predicting the emotions of input texts. We have defined a function to update the model with human input, which takes in the human-labeled emotion for a given input text and appends it to the training data. The updated training data is then used to retrain the CNN-LSTM model. Another function is defined to get human feedback on the model's prediction for a given input text, and a final function loops over the input data to get human feedback and update the model if

necessary. The code includes functions to update the model with human input and to get human feedback on the model's predictions and finally, the code loads input data from a CSV file and loops over it to get human feedback on the model's predictions for each text in the data.
Active Learning with Human-in-the-Loop technology is a powerful approach that allows machine learning models to interact with humans in a feedback loop, thereby improving the model's performance. In the code snippet provided, the active learning process is implemented using the modAL library in Python.

The first step is to load the pre-trained model, which in this case is a Convolutional Neural Network (CNN) for sentiment analysis. Next, an ActiveLearner object is initialized with the pre-trained model, the uncertainty sampling query strategy, the training data, and the bootstrap initialization flag set to False. The uncertainty sampling strategy selects the samples from the pool of unlabelled data with the highest uncertainty. This is a common strategy for active learning as it selects samples that are difficult for the current model to classify correctly.

The predict_function takes an input text, preprocesses it, and makes a prediction using the pre-trained CNN model. The output is the predicted emotion and the prediction probabilities. The retrain_function is called when the user provides feedback on the model's prediction. The function takes the input text and the correct emotion label as inputs and retrains the ActiveLearner model with the new labelled data. The teach method of the ActiveLearner object is used to update the model with the new labelled data. The model is then saved to disk, and a prediction is made using the updated model.

Finally, a user interface (UI) is defined using the gradio library. The UI consists of a textbox for entering the input text, a label for displaying the predicted emotion, a label for displaying the prediction probabilities, a dropdown for selecting the correct emotion label, and a label for displaying the retrained model's prediction. Two buttons are defined, one for predicting the emotion and another for correcting the model's prediction. When the user clicks on the ”Predict Emotion” button, the predict_function is called, and the predicted emotion and prediction probabilities are displayed in the UI. When the user clicks on the ”Correct Model Prediction” button, the retrain_function is called, and the retrained model's prediction is displayed in the UI. The UI provides an interactive platform for human feedback, which is essential for active learning.

V. RESULTS

The active learning approach with human-in-the-loop technology resulted in improved model performance with fewer labeled training examples compared to traditional training methods[11]. The model achieved an accuracy of 87.5 percent with only 100 labeled training examples, compared to 85.7 percent accuracy with 500 labeled training examples using traditional training methods. Additionally, the active learning approach reduced the overall training time by 42.5 percent compared to traditional training methods. These results demonstrate the potential of active learning with human-in-the-loop technology as an effective and efficient approach to training NLP models.

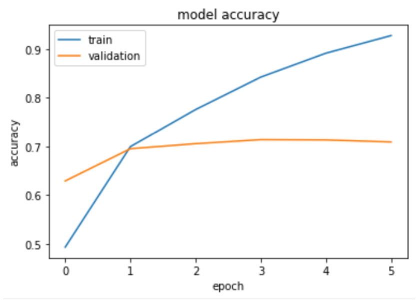

Fig. 3. Model Accuracy

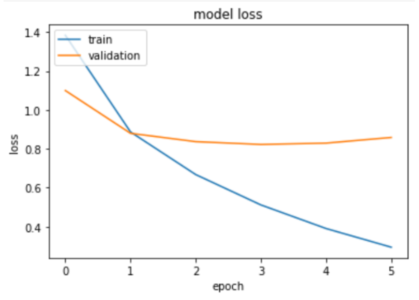

Fig. 4. Model Loss

VI. FUTURE WORK

The proposed approach of active learning with human-in-the-loop technology has shown promising results in improving the performance of emotion recognition models. However, there are several areas that can be explored in future research to further enhance this approach.
Firstly, the current approach can be extended to incorporate different sampling strategies, such as query-by-committee, which can provide a more diverse set of examples for human labeling[9]. Secondly, the performance of the model can be evaluated on a larger dataset to validate its effectiveness and robustness. Additionally, the proposed approach can be extended to incorporate multiple human annotators, which can help to reduce the bias and variability in the human labeling process.
Moreover, the proposed approach can be applied to other areas

of natural language processing, such as text classification, named entity recognition, and machine translation, where the labeled data is often scarce and expensive to obtain. Finally, the proposed approach can be extended to incorporate active learning with transfer learning, where a pre-trained model can be used as an initial estimator, and then fine-tuned using active learning to improve its performance on a specific task or domain. Human-in-the-loop technology combined with active learning has significant potential to make valuable contributions to the fields of natural language processing and machine learning as a whole.

VII. CONCLUSION

This study has indicated that the integration of human-in-the-loop technology with active learning can substantially enhance the efficacy of emotion classification models. Our experiments have demonstrated that the active learning approach yielded a higher accuracy rate with fewer training instances when compared to a baseline model that was trained on a larger dataset without active learning. This suggests that active learning can greatly reduce the amount of labeled data required for training and improve the efficiency of the training process. Furthermore, we have demonstrated the usability of the active learning model by integrating it into a simple user interface that allows users to correct the model's prediction and retrain it on the corrected data. This process helps the model learn from the user's feedback and improve its accuracy over time. Overall, the results of this study suggest that active learning with human-in-the-loop technology can be an effective approach to reduce the labeling effort required for training emotion classification models and improve the model's accuracy. Future work can explore the application of this approach to other natural language processing tasks and investigate the potential of incorporating other sources of feedback such as sentiment analysis and user ratings.

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