# Emotion Recognition from Formal Text (Poetry), II

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**Abstract: -**

The Experts in computational intelligence have focused less on classifying emotional states in poetry or formal text, in contrast to their emphasis on informal textual content such as SMS, email, chat, and online user reviews.

To address this gap, this study introduces a system for emotional state classification in poetry using state-of-the-art Artificial Intelligence technology known as Deep Learning. The system employs an attention-based C-LSTM model to analyze the poetry corpus and classify the text into various emotional states, such as love, joy, hope, sadness, anger, and others.

## I. INTRODUCTION

Experts in various fields, including natural language processing, computational linguistics, and computational intelligence, have shown interest in the classification of opinions, sentiments, and emotional states. There are two types of textual content that can be analyzed by machines: formal and informal. Formal textual content encompasses poetry, novels, essays, plays, and official/legal documentations, while informal textual content includes SMS, chat, and social media posts.

Detecting and classifying emotional states in formal text, particularly in poetry, can be a challenging task due to its complex nature. However, machine learning techniques, such as multi-label emotion classification, have been successfully applied to extract and analyze emotional states and themes from both formal and informal text. This is especially useful for classifying mixed data, which involves a combination of two or more languages.

Support Vector Machines (SVM) and a BiLSTM classifier are two methods that can be used to classify poetry into two emotional classes. However, an Attention-based C-LSTM model can further improve this classification by taking advantage of the Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and the Attention mechanism of deep learning. With this model, poetry can be classified into up to 5 emotional classes, allowing for a more accurate classification of emotional states in poetry. This is an extension from the baseline work and represents a significant improvement in the classification of emotional states in formal text.

## II. RELATED WORK

This section provides a brief overview of relevant studies on emotion classification in poetry text. In recent years, several researchers have conducted works in the field of emotion recognition using machine learning techniques. Sreeja and Mahalakshmi [1], for instance, developed an emotional state recognition system from poetry text by categorizing poetry text based on different emotion categories using the Naïve Bayes machine learning classifier.

Other approaches have also been tried, such as comparing SVM and Naïve Bayes algorithms to classify emotions from a poem. However, all models and approaches face a common problem, which is the limited dataset size.

To make the model more versatile, including different contexts or domains could be helpful. For example, incorporating phonemic features could enable the model to classify emotions from an audio file, such as music. Additionally, adding a speech-to-text converter could make the model useful as an interpreter between two individuals.

## III. LITERATURE SURVEY

| SNo. | Journal, Year | Author | Title | Abstract |
|---|---|---|---|---|
| 1. | IEEE, 2021 | Iqra Ameer, Geigori Sidorov | Multi-Label Emotion Classification on Code-Mixed Text: Data and Methods | Using ML, DL, transfer based learning to classify emotion in mixed data. |
| 2. | IEEE, 2021 | Chanf Liu, Taiao Liu, Shuojue Yang, and Yajun Du. | Individual Emotion Recognition Approach Combine Gated | Using BI-GRU to classify emotion. |

| | | | | |
|---|---|---|---|---|
| | | | Recurrent Unit with Emotion Distribution Model | |
| 3. | IEEE, 2020 | Hassan Alhuzali and Sophia Ananiadou | Improving Textual Emotion Recognition Based on Intra- and Inter-Class Variation. | Using Variant triplet center loss (VTCL) for emotion classification. |
| 4. | IEEE, 2019 | Erdenebileg Batbaatar, Meijing Li, and Keun Ho Ryu | Semantic Emotion Neural Network for Emotion Recognition from Text. | Using SENN model which can utilize both sematic/syntactic and emotional relationship information by adopting pre-trained word representation. |

*Table 1: Literature Survey*

## IV. METHODOLOGY AND MATERIALS

A. **The hardware requirements** for this project using ML models can vary depending on the size of the dataset and the complexity of the ML models, but some common requirements include:

- **Processor:** A multi-core processor with a high clock speed is recommended to handle the computational demands of running ML algorithms.
- **Memory:** A minimum of 8 GB of RAM is recommended, but more may be required depending on the size of the dataset and the complexity of the models.
- **Storage:** A solid-state drive (SSD) with sufficient storage space is recommended to store the dataset and the software required for the project.
- **Graphics Processing Unit (GPU):** A GPU may be required for the deep learning models, which are computationally intensive.

- **Operating System:** A 64-bit operating system, such as Windows 10 or Ubuntu, is recommended to support the software and libraries required for the project.

**B. The software requirements** for this project using ML models can vary depending on the size of the dataset and the complexity of the models used, but some common requirements include:

- **Programming Language:** A programming Language such as Python or R is necessary to implement the ML models.

- **Machine Learning Libraries:** A range of libraries and packages for ML, such as Pandas, NumPy, NLTK, Matplotlib, scikit-learn, etc. These libraries provide pre-built algorithms and functions for training, validation, and prediction.

- **Data analysis and visualization software:** Software such as R Studio or Jupyter Notebook is necessary for data analysis and visualization. This software can be used to explore the dataset, prepare the data for modelling, and visualize the results.

- **Database management software:** A database management system, such as SQLite or MySQL, may be required to store and manage the dataset.

## C. System Overview

Like any machine learning project, this project too is carried out in several steps as mentioned below:

- **Data Acquisition:** To train a deep learning model, one of the most important steps is to collect the data. The dataset should be large enough to train a model without introducing under training.

- **Data Pre-processing:** To implement the deep learning model, it is important to make sure that the data is fit for use. So, we must remove any noise, outliers, incorrect or incomplete data to make sure the result of our model is accurate.

  The next step is to transform the words into numbers. So, some of the basic pre-processing steps such as stop-words removal, conversion to lowercase, and tokenization, are performed. After tokenization, a vocabulary is built which transforms the sequences of words into the sequences of integers, where each integer represents a specific word in a vocabulary.

- **Feature Representation and Extraction:** To enable the model to learn, each word is transformed into an embedding vector and further, features are extracted from these embedded vectors which are received as input.

- The final step is to classify the input into multi-label classification (more than 2 classes are termed as multi-label).

## D. System Architecture

This section outlines the proposed architecture for the model designed to classify poetry into emotional classes, such as joy, anger, fear, sadness, and so on. The model receives input from a Python GUI application in the form of text and displays the result. Alternatively, a web-based frontend could also be developed for this project, which would communicate with the backend using HTTP request/response.

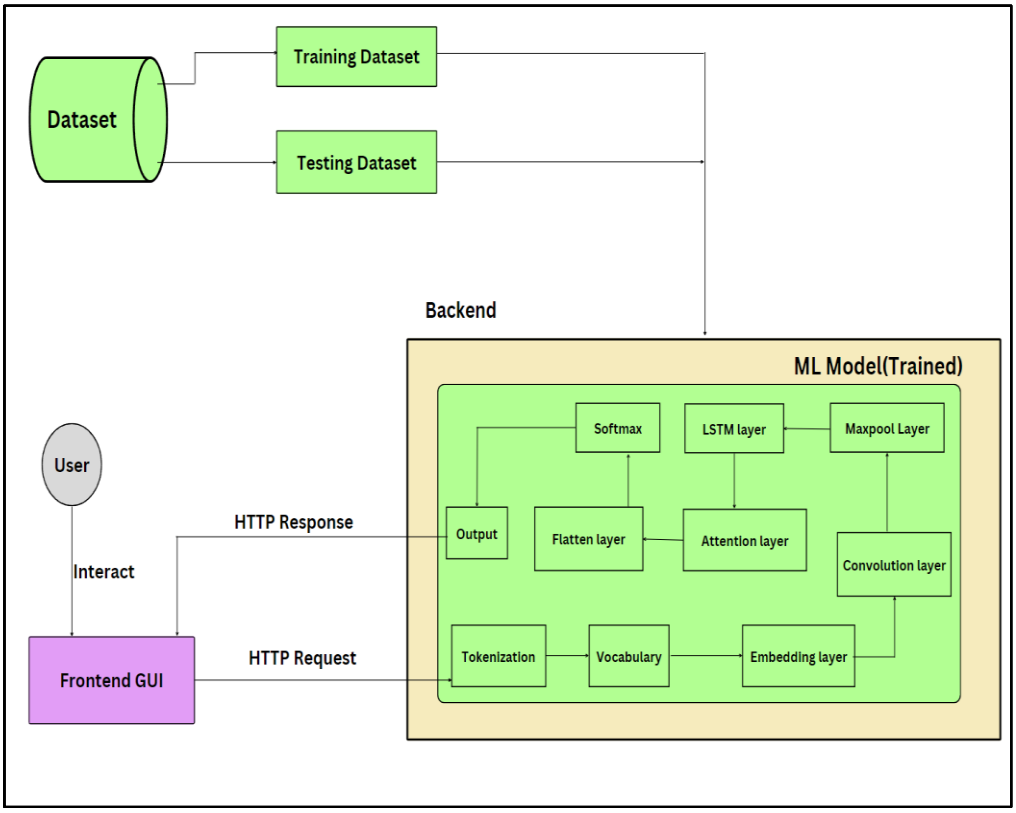


*Figure 1: System Architecture*

The proposed architecture consists of several layers:

- **Embedding Layer:** This layer uses pre-trained 300-dimensional word vectors from Wikipedia articles to represent text. This approach is better than training word vectors with our small dataset, as the pre-trained vectors already capture the similarity of words with similar meanings.
- **Deep Network:** This layer takes the sequence of embedding vectors and compresses them into a representation that captures all the information in the text. Typically, an RNN (or a variant like LSTM/GRU) is used for this part of the network. Dropout can be added to prevent overfitting.
- **Fully Connected Layer:** This layer takes the deep representation from the RNN/LSTM/GRU and transforms it into the final output classes or class scores. It consists of fully connected layers, batch normalization, and optional dropout layers for regularization.
- **Output Layer:** This layer uses either Sigmoid (for binary classification) or SoftMax (for both binary and multi-class classification) to produce the final output based on the problem at hand.

## V. MATHEMATICAL MODEL

The C-LSTM (Convolutional LSTM) algorithm is a variant of the LSTM (Long Short-Term Memory) algorithm that includes a convolutional layer to capture spatial information from input data. The C-LSTM model can be expressed mathematically as follows:

Let $x_t$ be the input vector at time step t, $h_t$ be the hidden state vector, and $c_t$ be the cell state vector.

The convolutional layer takes the input vector $x_t$ and applies a set of filters $w_k$ to it, producing a set of feature maps $f_k$. Each feature map is computed as:

$$f_k = w_k * x_t$$

where * denotes the convolution operation.

The LSTM layer then processes the feature maps to update the hidden state and cell state vectors as follows:

$$i_t = \sigma(W_i * f_t + U_i * h_{t-1} + b_i)$$

$$f_t = \sigma(W_f * f_t + U_f * h_{t-1} + b_f)$$

$$o_t = \sigma(W_o * f_t + U_o * h_{t-1} + b_o)$$

$g_t = \tanh(W_c * f_t + U_c * h_{t-1} + b_c)$

$c_t = i_t * g_t + f_t * c_{t-1}$

$h_t = o_t * \tanh(c_t)$

where $W_i$, $W_f$, $W_o$, $W_c$, $U_i$, $U_f$, $U_o$, and $U_c$ are weight matrices, $b_i$, $b_f$, $b_o$, and $b_c$ are bias vectors, σ is the sigmoid function, and tanh is the hyperbolic tangent function. The model can be trained using backpropagation through time and gradient descent to minimize a specified loss function.

## VI. ADVANTAGES

Some of the most common benefits of Emotional classification of formal text (poems) using ML is as following:

- **Scalability:** Manually analysing and organizing formal data is slow and much less accurate. ML can automatically classify huge number of texts in a matter of seconds.
- **Real-time analysis:** Not only poems but Formal text like legal documents can be analysed using this model to get observations from the text as soon as possible.
- This model can also help people from non-literature background understand poetry and take interest in what they are trying to read.
- This model can help reduce the bias present in individuals reading the text to correctly classify the text.

## VII. LIMITATIONS

Despite many advantages, ML model for emotional classification of formal text (poetry) comes with its own challenges. Few of those challenges are listed below:

- **Scheduling takes time:** It takes a significant amount of time before the model can be fully operational as training and testing the model takes time.
- **Computationally intense:** Executing the model can be computationally intense as it requires significant number of resources like RAM, processing power, etc.

- **Skilful interpretation of results:** Even if we can generate results from the model, there is still a need of a skilled individual to interpret the results correctly.

- **Language barrier:** Two poems can be different from each other if two different individuals have written it. So, the same words in different poems can mean different things, and can be classified under different emotions, so that can be a problem.

## VIII. CONCLUSION AND FUTURE WORK

The objective of this study was to explore different approaches for classifying emotional states in formal text, specifically poetry, using machine learning algorithms. By analyzing previous research, the study gained a better understanding of the problem and identified which algorithms could be effective. After deploying the model, further evaluations will be carried out to assess its accuracy and identify opportunities for improvement to ensure that the model delivers precise and valuable results..

## IX. REFERENCES

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