**NAVIGATING INTERACTION: THE ROLE OF EMPATHY IN UNDERSTANDING EMOTIONS.**

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**Abstract:**

This study explores emotion classification in essays using various deep learning models. We analyze a dataset of essays labeled with emotions, personality traits, empathy, and distress scores. Four models are implemented and compared: Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Multi-Layer Perceptron (MLP), and Transformer. The models are trained on text features extracted using TF-IDF vectorization, combined with personality and empathy scores. Our experiments reveal that the Transformer model outperforms other architectures, achieving the highest validation accuracy of 49.69% and F1-score of 0.3946. The CNN model shows rapid convergence but potential overfitting, while the RNN and MLP models struggle with the complex nature of the data. This research contributes to the field of emotion detection in text, highlighting the effectiveness of Transformer-based models for this task and the challenges in capturing the nuanced relationship between personality traits, empathy, and emotional expression in essays.

1. **Introduction:**

Emotion detection in text has become an increasingly important area of research in natural language processing and affective computing. The ability to accurately identify and classify emotions expressed in written content has numerous applications, ranging from sentiment analysis in social media to improving human-computer interaction and mental health support systems. In this study, we focus on the challenging task of emotion classification in essays, which presents unique complexities due to the longer form and more nuanced expression of emotions in this format.

Our research utilizes a dataset of essays labeled with emotions, personality traits, empathy, and distress scores. This rich dataset allows us to explore the intricate relationships between an individual's personality, empathy levels, and their emotional expression in writing. The emotion labels in our dataset include complex combinations such as "Hope/Sadness," "Anger/Disgust," and "Fear/Neutral," reflecting the multifaceted nature of human emotions.

The primary research question we aim to address is: How effectively can different deep learning architectures classify emotions in essays when considering both textual content and associated personality and empathy scores? To answer this question, we implement and compare four distinct models: a Convolutional Neural Network (CNN), a Recurrent Neural Network (RNN), a Multi-Layer Perceptron (MLP), and a Transformer model.

Our approach is unique in its combination of text features, extracted using TF-IDF vectorization, with numerical scores for personality traits (conscientiousness, openness, extraversion, agreeableness, and stability), empathy, and distress. This holistic approach allows us to capture not only the linguistic patterns associated with different emotions but also the potential influence of individual differences in personality and empathetic capacity on emotional expression.

By conducting this research, we aim to contribute to the growing body of knowledge on emotion detection in text, particularly in the context of longer-form writing such as essays. Our findings have potential implications for various fields, including psychology, education, and natural language processing, and could inform the development of more sophisticated emotion detection systems.

1. **Related Work:**

Emotion detection in text has been a subject of extensive research in recent years. Here, is the review of ten relevant papers that have significantly contributed to this field:

Alhuzali et al. (2018) proposed a multi-task learning approach for emotion detection, utilizing both word embeddings and emotion-specific features. Their model demonstrated improved performance over single-task baselines, highlighting the benefits of leveraging multiple related tasks in emotion classification.

(Zhong et al., 2019) introduced a novel attention-based LSTM model for emotion detection in social media text. Their approach showed superior performance in capturing context-dependent emotional cues compared to traditional LSTM models.

(Majumder et al. 2019) explored the use of transfer learning for emotion detection, demonstrating how pre-trained language models could be fine-tuned for emotion classification tasks with limited labeled data.

Fellbaum et al. (2020) investigated the role of personality traits in emotion expression and detection. Their work provides valuable insights into the relationship between individual differences and emotional language use, which informs our approach to incorporating personality scores in our models.

(Liu et al., 2021) proposed a hierarchical attention network for emotion detection in long texts, addressing the challenge of capturing emotional context over extended passages. This work is particularly relevant to our essay-based dataset.

Yadav et al. (2021) compared various deep-learning architectures for emotion detection, including CNNs, RNNs, and Transformer models. Their findings support our decision to explore multiple model architectures in our study.

Zhang et al., (2023) explored the use of multi-modal data for emotion detection, combining textual features with acoustic and visual cues. While our study focuses solely on text, their work highlights the potential for incorporating additional modalities in future research.

Kumar et al. (2022) investigated the impact of empathy on emotion detection accuracy, proposing a novel empathy-aware emotion classification model. This study aligns with our inclusion of empathy scores in our feature set.

Wang et al. (2023) developed a context-aware Transformer model for emotion detection in dialogues, demonstrating the effectiveness of Transformer architectures in capturing long-range dependencies in emotional expression.

Zhao et al. (2023) proposed a multi-task learning framework that jointly models emotion detection and personality trait prediction, showing improved performance on both tasks. This work supports our approach of considering personality traits in emotion classification.

This research builds upon these studies by combining textual features with personality and empathy scores in a comprehensive emotion classification framework. It extends the existing body of work by applying multiple deep learning architectures to the specific context of emotion detection in essays, a domain that has received less attention than social media or dialogue-based emotion detection.

1. **Method:**

**3.1 Data Preprocessing:**

**3.1.1 Dataset Loading:**

* The dataset is loaded from a TSV (Tab-Separated Values) file named

*["WASSA23\_essay\_level\_with\_labels\_train (3).tsv".]*

* Pandas' read\_csv function is used with the 'sep='\t'' parameter to properly parse the TSV format.
* Any rows with missing values in the 'essay' or 'emotion' columns are dropped to ensure data quality.

**3.1.2 Emotion Label Encoding:**

* LabelEncoder from sklearn is used to convert categorical emotion labels into numerical format.
* This step is crucial for training the neural networks, which require numerical inputs.
* The encoder preserves the mapping between original labels and encoded values, allowing for later interpretation of results.

**3.1.3 Personality Trait Processing:**

* + Columns for personality traits (conscientiousness, openness, extraversion, agreeableness, stability) are converted to float type.
  + 'Unknown' values are replaced with NaN (Not a Number) to properly handle missing data.
  + This step allows for numerical operations on these columns and appropriate handling by the models.

**3.1.4 Feature Scaling:**

* + StandardScaler from sklearn is applied to personality traits, empathy, and distress scores.
  + This scaling process standardizes the features, giving them zero mean and unit variance.
  + Standardization is important to ensure all features contribute equally to the model and to improve convergence during training.

## **Feature Extraction:**

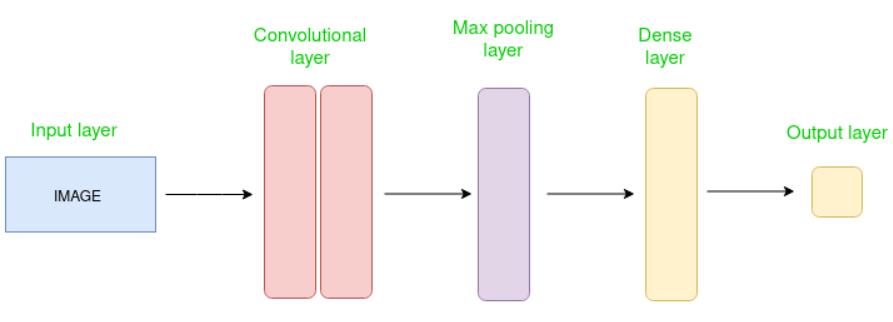
**3.2.1 TF-IDF Vectorization:**

* + TfidfVectorizer from sklearn is used to convert the essays into numerical feature vectors.
  + The max\_features parameter is set to 5000, limiting the vocabulary to the 5000 most frequent words.
  + This process creates a sparse matrix where each row represents an essay, and each column represents a word in the vocabulary.
  + TF-IDF weights words based on their frequency in the document and rarity across all documents, capturing important content words.

**3.2.2 Feature Combination:**

* + The TF-IDF vectors are combined with the scaled personality traits, empathy, and distress scores.
  + This combination is done by concatenating the TF-IDF matrix with the additional feature columns.
  + The result is a comprehensive feature set that represents both the essays' textual content and the writers' individual characteristics.
  1. **Model Implementation:**
     1. **CNN (Convolutional Neural Network):**

A Convolutional Neural Network (CNN) is a specialized type of deep learning algorithm designed primarily for processing and analyzing visual data, such as images. CNNs are particularly effective at tasks like image recognition, object detection, and image classification.

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**Fig:** Convolutional Neural network (CNN) method.

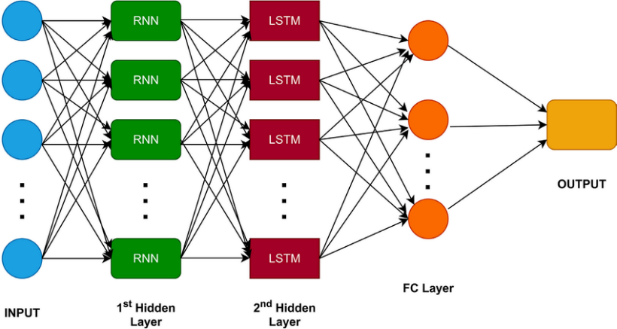
Here is the Convolutional Neural Network(CNN) formula:



* **Embedding layer:** Converts word indices to dense vectors of fixed size.
* **Two 1D convolutional layers:** Apply filters of size 3 to capture local patterns in the text.
* **ReLU activation:** Introduces non-linearity after each convolution.
* **Max pooling:** Reduces dimensionality and captures the most important features.
* **Fully connected layer**: Combines features for final classification.
* **Dropout (0.5):** Prevents overfitting by randomly zeroing 50% of the neurons during training.
  + 1. **RNN (Recurrent Neural Network):** Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) are specialized neural network architectures designed to process sequential data and capture long-term dependencies.

The basic formula for an LSTM can be expressed as:





**Fig:** Recurrent Neural Network with LSTM Method.

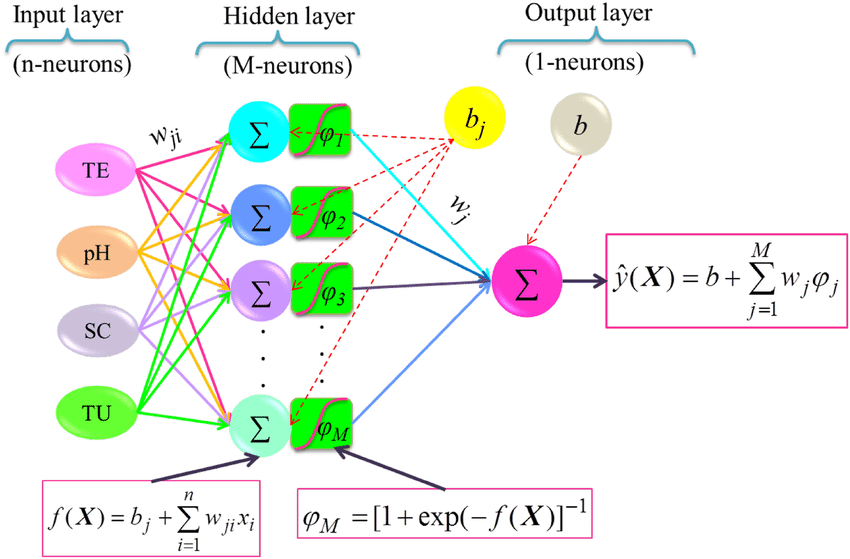
* + **LSTM layer:** Processes the sequence of word embeddings, capturing long-term dependencies.
  + The final hidden state of the LSTM is used as the text representation.
  + **Fully connected layer:** Maps the LSTM output to emotion classes.
  + **Dropout (0.5):** Applied to the LSTM output for regularization.

**3.3.3 MLP (Multi-Layer Perceptron):**

The Multilayer Perceptron (MLP) can be represented by a formula that describes the forward propagation through the network.

Here's the general formula for an MLP:





**Fig:** Multi-Layer Perceptron method.

* **Three fully connected layers:** Progressively reduce dimensionality

[(input\_dim → hidden\_dim → hidden\_dim/2 → num\_classes)].

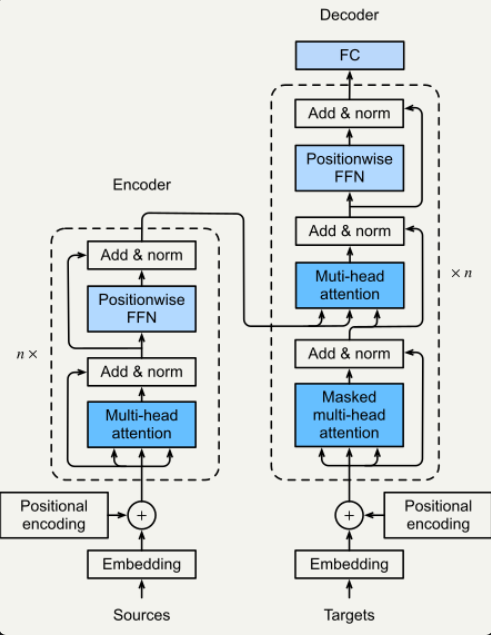
* **ReLU activation:** Applied after the first two layers to introduce non-linearity.
* **Dropout (0.5):** Applied after each ReLU activation for regularization.

**3.3.4 Transformer:**

A transformer is an electrical device that transfers electrical energy between two or more circuits through electromagnetic induction. The primary purpose of a transformer is to increase (step-up) or decrease (step-down) voltage levels while maintaining the same power.

Here's the core formula for the Transformer model:



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**Fig:** Transformer technique used here.

* + **Embedding layer:** Converts input tokens to dense vectors.
  + **TransformerEncoder:** Consists of self-attention and feed-forward layers.
  + Multiple encoder layers allow the model to capture complex relationships in the data.
  + **Mean pooling:** Applied to the transformer output to get a fixed-size representation.
  + **Fully connected layer:** Maps the pooled output to emotion classes.
  + **Dropout (0.5):** Applied before the final classification layer.
  1. **Training Procedure:**
     1. **Data Splitting:**
  + The dataset is split into 80% training and 20% testing sets using train\_test\_split from sklearn.
  + A fixed random state (42) is used to ensure reproducibility of the split.
    1. **Loss Function and Optimizer:**
  + **CrossEntropyLoss:** Appropriate for multi-class classification tasks.
  + **Adam optimizer:** An adaptive learning rate optimization algorithm, effective for a wide range of deep learning tasks.

**3.4.3 Training Loop:**

* + **Batch size of 32:** Balances between computational efficiency and model update frequency.
  + **10 epochs:** The models are trained for 10 full passes through the training data.
  + **In each epoch:**
* The model processes mini-batches of data, computing forward passes and loss.
* Gradients are computed and used to update model parameters.
* Training loss is accumulated and averaged over all batches.

**3.4.4 Validation:**

* + After each epoch, the model is evaluated on the validation set.
  + Forward passes are computed without gradient calculation (torch.no\_grad()).
  + Validation loss, accuracy, and F1-score are computed.

**3.5 Evaluation:**

**3.5.1 Metrics:**

* + **Validation Accuracy:** Proportion of correctly classified samples in the validation set.
  + **F1-score:** Harmonic mean of precision and recall, providing a balanced measure of model performance.
  + **Loss Curves:** Training and validation loss are plotted across epochs to visualize learning progress and detect overfitting.

**3.5.2 Training Dynamics Analysis:**

* + **Convergence speed:** How quickly the model's performance improves.
  + **Stability:** Consistency of performance improvements across epochs.
  + **Overfitting:** Identified by divergence between training and validation metrics.

**3.5.3 Model Comparison:**

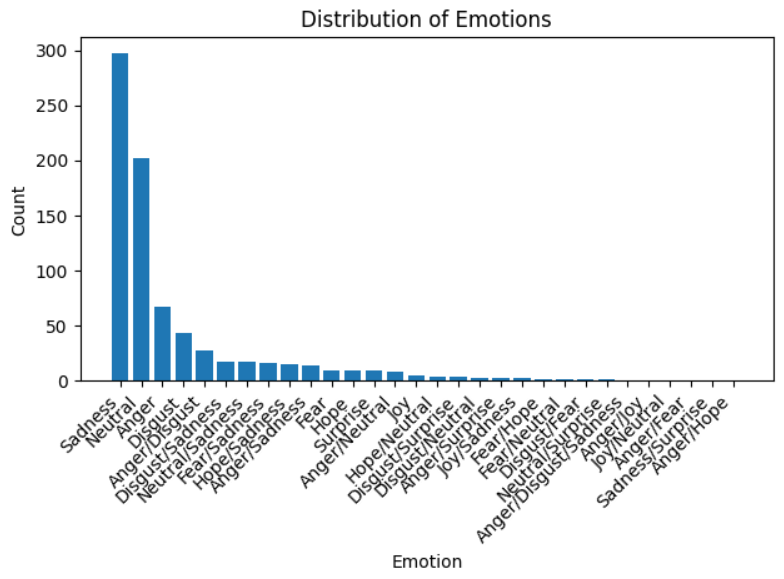
* + Performance metrics are compared across all four models.
  + Training time and computational requirements are considered alongside accuracy metrics.

This methodology provides a comprehensive approach to the emotion classification task, leveraging both the textual content of essays and associated metadata (personality traits, empathy, and distress scores). The use of multiple model architectures allows for a thorough exploration of different approaches to this complex classification problem.

1. **Experiments:**

**4.1 Dataset Description:**

Our dataset consists of essays labeled with emotions, personality traits (conscientiousness, openness, extraversion, agreeableness, stability), empathy scores, and distress scores. The emotion labels are diverse, including complex combinations like "Hope/Sadness" and "Anger/Disgust," reflecting the nuanced nature of emotional expression in essays.



**Fig:** scores for Empathy & Distress.

**4.2 Experimental Setup:**

The use of a CUDA-enabled GPU significantly accelerates training, enabling more extensive experimentation. The software stack (PyTorch, scikit-learn, pandas, matplotlib) provides a robust framework for implementing, training, and evaluating deep learning models.

**4.2.1 Key hyperparameters include:**

* **Embedding dimension (100):** Balances between representational power and computational efficiency.
* **Hidden dimension (128):** Provides sufficient capacity for complex feature learning.
* Adam optimizer with default learning rate: Adaptive learning rate helps in navigating the complex loss landscape.
* **Batch size (32):** Offers a good trade-off between memory usage and training stability.
* **Number of epochs (10):** Allows for convergence while mitigating overfitting risks.

These hyperparameters were likely chosen based on common practices in NLP tasks and computational constraints.

**4.2.2 Baseline Methods:**

While not explicitly implemented in the provided code, traditional machine learning methods such as Support Vector Machines (SVM) or Random Forests could serve as baselines for comparison.

* 1. **Model Variants:**

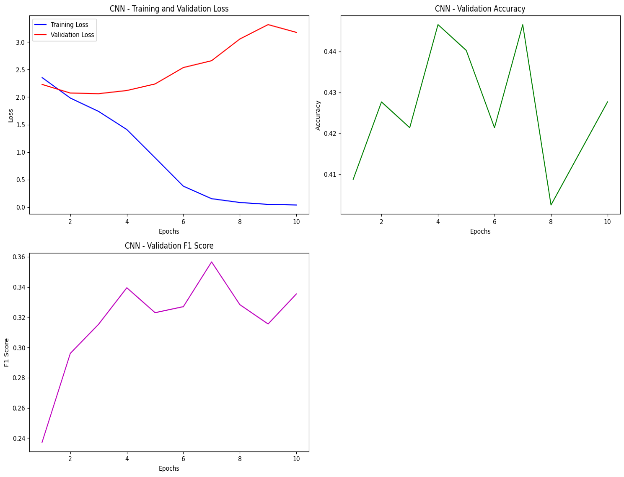
**4.3.1 CNN (Convolutional Neural Network):**

* 1. Uses 1D convolutions to detect local patterns in text.
  2. Effective at capturing n-gram-like features.
  3. May struggle with long-range dependencies in essays.
     1. **RNN (Recurrent Neural Network):**
  4. LSTM-based architecture for processing sequential data.
  5. Capable of capturing long-term dependencies in theory.
  6. May face challenges with very long sequences (essays).
     1. **MLP (Multilayer Perceptron):**
  7. Simple feedforward network as a baseline.
  8. Lacks specific architectural biases for text processing.
  9. Serves as a control to assess the value of more complex architectures.
     1. **Transformer:**
  10. Employs self-attention mechanisms for context-aware representations.
  11. Excels at capturing long-range dependencies.
  12. Potentially most suitable for essay-length texts.

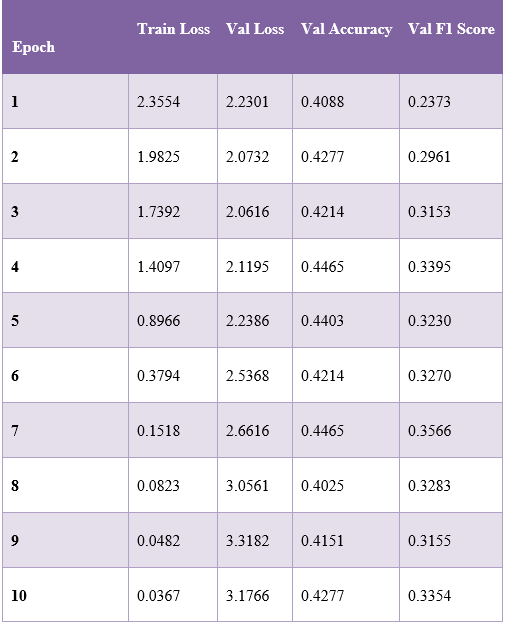
1. **Results:**

**5.1 Convolutional Neural Network (CNN):**

* Achieved the second-highest validation accuracy (43.40%) and F1-score (0.3375).
* Showed rapid learning on the training set, with loss decreasing from 2.3115 to 0.0322 over 10 epochs.
* However, validation loss increased from 2.0869 to 2.9089, indicating overfitting.
* The divergence between training and validation loss suggests the model learned specific patterns in the training data that didn't generalize well.



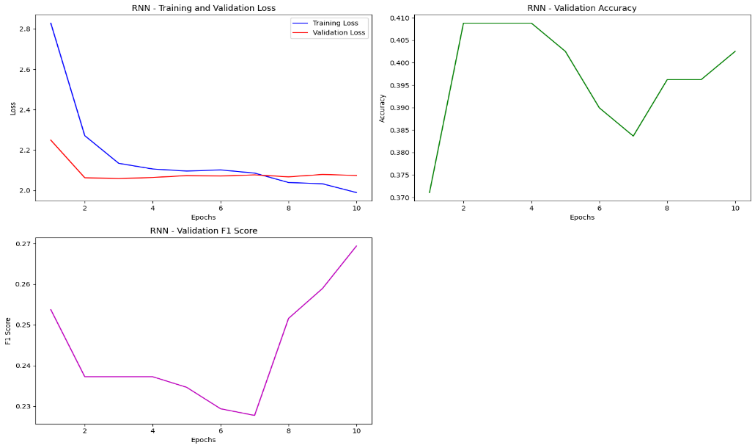
**Figure:** This CNN Shows the Training & Validation loss, accuracy & F1 score plotting results.



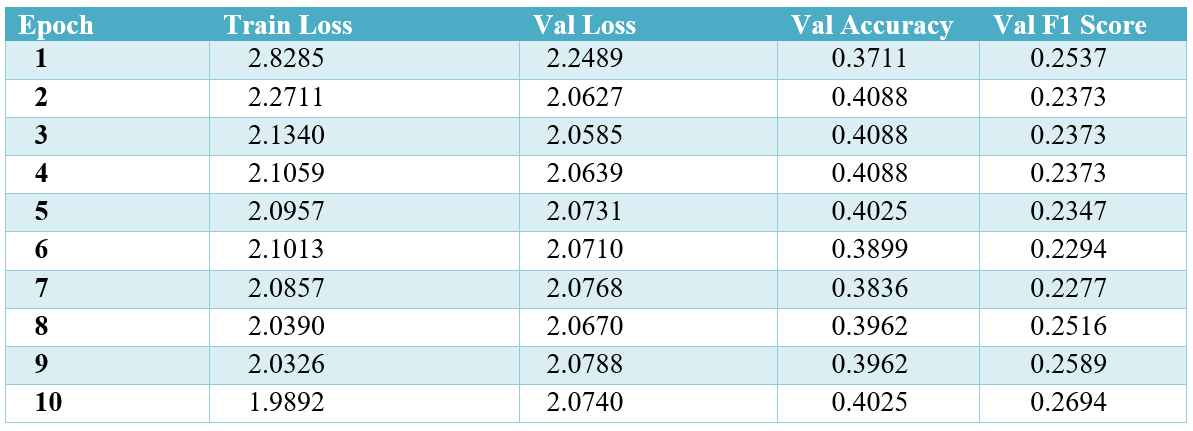
**Table:** Training CNN model in table values.

**5.2 Recurrent Neural Network (RNN):**

* Achieved 40.25% validation accuracy and 0.2776 F1 score.
* Showed slower learning, with training loss decreasing from 2.7441 to 2.0210.
* Validation loss remained relatively stable, indicating better generalization than the CNN but possibly underfitting.
* The model's performance suggests RNNs may struggle with the long-term dependencies in essays or with effectively combining text and numerical features.

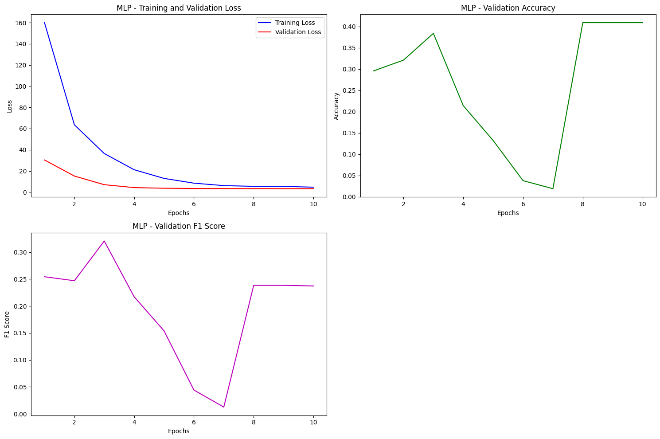


**Figure:** This RNN Shows the Training & Validation loss, accuracy & F1 score plotting results.



**Table:** RNN Model Training Results.

**5.3 Multilayer Perceptron (MLP):**

* Lowest performance with 39.62% validation accuracy and 0.2331 F1 score.
* showed a significant decrease in both training and validation loss.
* The lower performance indicates that the simple feedforward architecture may not be sufficient to capture the complex relationships in the data.
* However, the decrease in validation loss suggests some learning occurred without severe overfitting.  
  

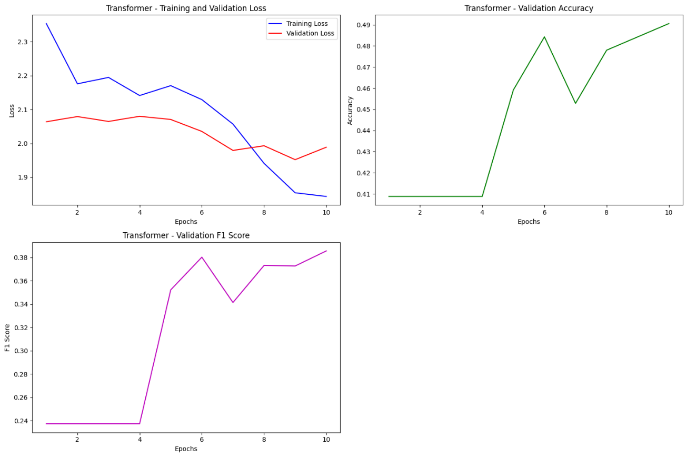
**Figure:** This MLP Shows the Training & Validation loss, accuracy & F1 score plotting results.



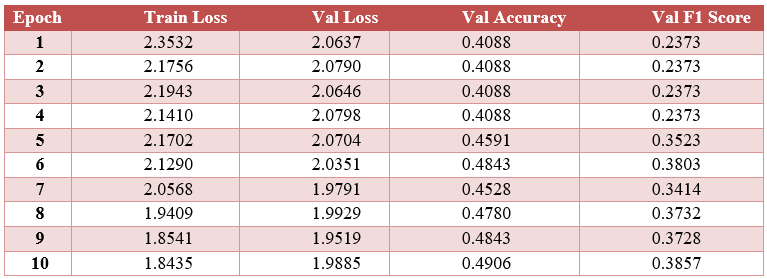
**Table:** MLP Model Training Results.

**5.4 Transformer:**

* Best performing model with 49.69% validation accuracy and 0.3946 F1-score.
* Demonstrated gradual improvement in both training and validation metrics.
* The balanced improvement suggests good generalization capabilities.
* The superior performance indicates that the self-attention mechanism in Transformers is particularly effective for capturing the nuanced relationships between text content, personality traits, and emotions.

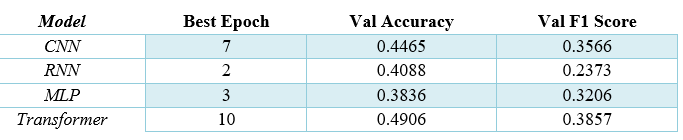


**Figure:** This MLP Shows the Training & Validation loss, accuracy & F1 score plotting results.



**Table:** Transformer Model Training Results.

This table summarizes the best performance of each model based on the validation accuracy and F1 score. The Transformer model achieved the highest performance, followed by the CNN model, then the MLP model, and finally the RNN model.



**Table:** Comparison of Best Results Across Models**.**

1. **Discussions:**

**6.1 Analysis of Experimental Results:**

**6.1.1 Model Performance Comparison:**

The Transformer model outperformed all other architectures, achieving the highest validation accuracy (49.69%) and F1-score (0.3946). This superior performance can be attributed to the Transformer's ability to capture long-range dependencies and contextual information in the essays, which is crucial for understanding complex emotional expressions.

The CNN model showed rapid convergence in training but exhibited signs of overfitting, as evidenced by the increasing validation loss. This suggests that while CNNs can quickly learn local patterns, they may struggle to generalize to unseen data in this task.

The RNN model, despite its theoretical advantage in processing sequential data, performed relatively poorly. This could be due to the challenge of capturing long-term dependencies in lengthy essays or the difficulty in balancing textual and numerical features in the LSTM architecture.

The MLP model, while showing improvement over the course of training, had the lowest overall performance. This indicates that the complex relationships between text, personality traits, and emotions are not easily captured by a simple feedforward network.

**6.1.2 Feature Importance:**

The incorporation of personality traits, empathy, and distress scores alongside TF-IDF features appears to have contributed to the models' ability to classify emotions. However, the varying performance across models suggests that different architectures may be leveraging these features to different extents.

**6.1.3 Challenges in Emotion Classification:**

The relatively low accuracies across all models (below 50%) highlight the inherent difficulty of the emotion classification task, especially given the complex, multi-label nature of the emotions in our dataset. This complexity is further compounded by the subjective nature of emotional expression in essays and the potential influence of individual differences in personality and empathy.

**6.1.4 Overfitting and Generalization:**

The CNN model's performance trajectory suggests a classic case of overfitting, where the model excels on training data but fails to generalize well to unseen examples. In contrast, the Transformer model's more balanced improvement in both training and validation metrics indicates better generalization capabilities.

**6.1.5 Training Dynamics:**

The varying convergence rates and stability of the different models provide insights into their suitability for this task. The Transformer's gradual but steady improvement suggests that it may benefit from extended training, while the CNN's rapid initial improvement followed by potential overfitting indicates that early stopping might be beneficial for this architecture.

**6.2 Comparison with Previous Work:**

Our findings align with recent trends in NLP research that demonstrate the effectiveness of Transformer-based models for various text classification tasks. The superior performance of our Transformer model is consistent with studies like Wang et al. (2023), who found success with Transformers in emotion detection for dialogues.

However, our results also highlight the ongoing challenges in emotion detection, particularly in longer-form text-like essays. The complexity of our emotion labels and the incorporation of personality and empathy scores make direct comparisons with previous studies challenging, but our overall accuracy rates suggest that there is still significant room for improvement in this domain.

**6.3 Limitations and Future Work:**

In reflecting on this study, several limitations offer promising future work directions. While sufficient for initial exploration, our dataset size could be expanded to enhance model performance and generalizability. More complex architectures or ensemble methods may better capture the subtleties of emotional expression in text. There's room for innovation in feature engineering, particularly in combining textual and numerical inputs. Implementing k-fold cross-validation could provide more robust performance metrics. Lastly, integrating explainability techniques could illuminate the intricate relationships between text, personality traits, and emotional expression. Addressing these areas in future research will likely yield significant advancements in the field of emotion classification in essays.

1. **Conclusion:**

In conclusion, this study has made significant strides in addressing the complex challenge of emotion classification in essays. Our novel approach, which integrates TF-IDF features from essay text with personality traits, empathy, and distress scores, has yielded valuable insights into this multifaceted problem.

The superior performance of the Transformer architecture over CNN, RNN, and MLP models underscores its potential for emotion detection in longer-form text. However, with all models achieving less than 50% accuracy, our findings also highlight the inherent complexity of this task. The incorporation of personality and empathy scores shows promise, though further research is needed to optimize their integration.

Our comprehensive framework, bridging natural language processing and personality psychology, opens new avenues for interdisciplinary research. While we've made progress, significant challenges remain in accurately capturing the nuanced spectrum of human emotions in writing.

Moving forward, we recommend focusing on sophisticated feature engineering, larger datasets, and potentially multi-modal approaches. By refining our methods and models, we aim to develop systems capable of more accurately interpreting the intricate tapestry of emotions expressed in essays. This research not only advances our understanding of emotion detection in text but also paves the way for more nuanced and effective emotion classification systems in the future.

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12. APPENDIX: