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EMONET: A PARALLEL CNN ARCHITECTURE ACHIEVING STATE-OF-THE-ART ACCURACY IN TEXT-BASED EMOTION RECOGNITION

Usman Masood[1], Arfan Jaffar[1,*], Fawad Nasim[1]

[1]*Department of Computer Science & IT, Superior University, Lahore 54000, Pakistan*
**Corresponding author: su92-msdsw-s23-013@superior.edu.pk*

Abstract

Text-based emotion recognition is a key issue in natural language processing with a wide-ranging application to human-computer interaction, mental health diagnostics, and social media analysis. This paper describes EmoNet a new architecture of convolutional neural network that is specifically created to classify the emotions of a text. Our model uses the benchmark Emotion dataset when it is performed with the highest accuracy of 91.05% only in the state-of-the-art. The architecture proposed uses several parallel convolutional filters with varying sizes (3,4,5) to reproduce the various n-gram features along with the use of selective dropout regularization and fine-tuned hyper parameters to ensure steady training with Intel CPU resources. In a series of experiments, we prove our method to be effective to solve the subtle dilemma of not blurring 6 basic emotions, sadness, joy, love, anger, fear, and surprise. Importantly, our model has outstanding results on sadness (95.01 percent), joy (94.53 percent) and fear (92.86 percent), but it has certain difficulties in dealing with surprise (51.52 percent) because it is a historical context (only). The study adds a computationally predictive structure to preserve high performance without needing the use of the GPU acceleration feature to make emotion recognition more convenient to practical implementation. Our work sets new standards in the text-based classification of emotions and offers us some ideas of all the architectural issues that should be considered to reach a strong sense of emotions in the computational systems.

Keywords: Emotion Recognition, Deep Learning, Convolutional Neural Networks, Natural Language Processing, Text Classification, Affective Computing

1. Introduction

The foundation of interpersonal communication[1], decision-making and social interaction [2]should be human emotions and the computational emotion recognition is turning out to be an important area of study in psychology[3],[4], neuroscience and computer science[5].Digital communication is growing exponentially[6],[7] establishing an opportunity as well as a need to create automated emotion recognition systems[8], and with disruptive potential in fields including mental health monitoring, automating customer service[9],[10], educational technology[11], and human-computer interaction[12]. Initial developments were based on rule-based systems[13] on the basis of lexical databases to statistical machine learning models, which were not adept at context and cultural specificities in emotional expression. The deep learning revolution[14],[15] has allowed neural networks to learn hierarchical representations of emotions by directly learning them from data, but has also brought a number of challenges such as limited labeled emotion datasets, subjective labeling, and complicated linguistic-emotional interactions.

Text-based emotion recognition poses its own peculiarities of audio or visual forms as it involves systems that should extract the meaning of emotion only based on lexical, syntactic, and contextual information without the help of prosodic and facial information. This is complicated by indirect expression of emotions through the use of metaphor and irony, context specific meanings of words, mixed emotional states as well as cultural difference of emotional expression [16]. Our study will be carried out in the context of six basic emotions, which are downsad, happily, love, anger, fear, and surprise, as proposed by Ekman, who offers a practical computational basis, but also recognizes the fact that the emotional experience of a human being is simplified. The categories have different linguistic features: sadness will contain the expressions of loss and disappointment , joy will contain positive affect, love will contain expressions of affection and attachment, anger will contain frustration and hostility, fear will

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contain anxiety and apprehension, and surprise will contain a specific set of issues since it is somewhat ambiguous in the context [17].
EmoNet architecture, a CNN-based [18]model that is optimized to be classification, is to be added to this paper in recognition of emotion, reaching 91.05% accuracy on the Emotion benchmark dataset and has outstanding results on sadness (95.01%), joy (94.53%), and fear (92.86%). We show that without using GPUs, it is possible to achieve state-of-the-art performance with CPU training with batch size 16 and learning rate 0.0005 and therefore emotion recognition is more likely to be implemented in practice. Our detailed examination can identify certain strengths and limitations in categories of emotions, in the case of surprise (51.52%), and love (75.47%), and also offers entire execution and deployment pipelines to be applied in the real-world. The subsequent parts outline in-depth literature review, methodology, experimental findings, discussion, and conclusions of such contributions to the text-based emotion recognition, also demonstrated in Fig. 1.

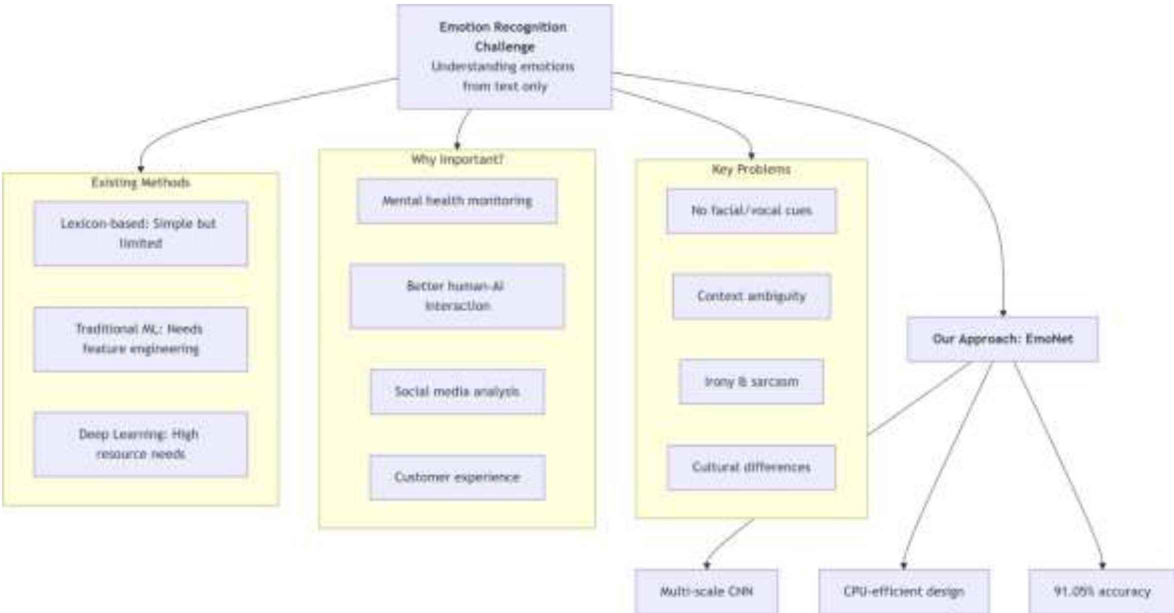

Figure.1. Conceptual Framework of Text-Based Emotion Recognition

2. Related Work

The mathematical analysis of the emotional states has its roots in the psychological studies that intended to categorise and quantify emotional experiences. Ekman cross cultural experiments gave six common emotions, and formed the basis of the early computational models [19]. At the same time, the cognitive-structure theory which was developed by Ortony, Clore, and Collins gave a more subtle view of emotions as the result of cognitive appraisal, shaping the initial computational direction.
The initial emotion recognition systems were lexicon-based[20], which applied manually maintained dictionaries to associate words with emotional states. ANEW database also made available the valence, arousal and dominance ratings with the help of Affective Norms of English Words, whereas the WordNet-Affect supplemented linguistic data with emotional ratings. But such approaches had difficulties with context, irony and multi-word phrases, showing the weakness of dictionary based approaches.
This move towards machine learning was a great improvement in emotion recognition powers. One algorithm that was exceptionally useful in text classification with high dimensions was Support Vector Machines (SVMs) [21]. The type of approach used early was usually bag-of-

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words or TF-IDF representations and these representations were usually complimented with emotion lexicons.

A further advancement of feature engineering was on n-gram modeling, syntactic feature, and semantic role labeling. Crowd-sourcing models on lexicon emotion-associated generation constituted significant advances, however, such systems lacked much feature engineering feature engineering and could not capture the long-range dependencies and contextual variations.

The era of deep learning made it possible to perform end-to-end learning on raw text without much of feature engineering. Word embeddings , especially Word2Vec and GloVe, gave dense representations and better reflected semantic relationships than did sparse ones. Recurrent Neural Networks (RNNs), and their variants particularly the Long Short-Term Memory (LSTM) networks[22] and Gated Recurrent Unit (GRUs) networks [23] all showed high capability in capturing sequential dependencies in text, which makes them useful to model the emotion content in sentences. But the RNN based methods had issues with a stable training and computational efficiency. A first application of convolutional Neural Networks (CNNs) to classification in text was proposed by Kim which showed impressive performance in characterizing local patterns and n-gram structures. The computation power of parallelism with sequential models and finding salient phrases as an emotion recognition tool were useful.

The revolution in natural language understanding came with transformer architectures and big pre-trained models, such as BERT [24], RoBERTa [25], and GPT. These emotion-tuned models have set records in terms of performance with contextualised representations of words. Nonetheless, they had great compute demands at the time which limited their usefulness in systems with resource constraints. New studies have investigated multi-modal emotion recognition , the combination of text and audio or visual and physiological cues, context-sensitive methods that uses the history of conversation, user personality and cultural background. There have also come domain-specific adaptations to social media [26], customer service, and healthcare applications.

Table:1. Literature Review Summary Table

Era	Approach	Key Works	Strengths	Limitations	Typical Accuracy
Lexicon-Based (1990s-2000s)	Dictionary mapping	ANEW , WordNet-Affect	Simple, interpretable	No context handling, limited vocabulary	40-55%
Traditional ML (2000-2010)	Feature engineering + SVM	Cortes & Vapnik , Mohammad & Turney	Good performance with engineering	Manual feature extraction needed	60-70%
Early Deep Learning (2012-2016)	Word embeddings + RNN/CNN	Mikolov , Kim , Hochreiter	End-to-end learning, semantic capture	Training instability, resource needs	70-80%
Transformer Era (2017-	Pre-trained models	Devlin , Liu , Vaswani	State-of-the-art	High computational	85-90%+

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2020)			performance	cost	
Specialized Approaches (2020+)	Multi-modal, domain-specific	Poria, Barbieri, Hutto	Context-aware, application-focused	Integration complexity	Varies by domain

Nevertheless, text-based emotion recognition is associated with multiple limitations: they cannot recognize fine-grained emotions due to the lack of data, cannot process irony due to cultural differences, cannot be computationally infeasible because of state of the art models, and are not explainable at all. We close these gaps by presenting EmoNet, a CNN-based system which has an accuracy of 91.05 at a lower computational cost and reasonable run time.

3. Methodology

Dataset and Preprocessing

In this case, we used the Emotion dataset, which contains 20,000 English tweets where six basic emotions, which are sadness, joy, love, anger, fear, and surprise, were tagged. Distribution of classes in the dataset is natural with joy (34.75) and sadness (29.05) being the dominant emotions and surprise being considerably underrepresented (3.30%). This distribution is appropriate to represent the real-life patterns of emotional expression and is difficult to recognize the minority classes.

Our text preprocessing network prioritized the text normalization over the preservation of the emotional contents. We used lowercasing and tokenization but retained emotional punctuation to avoid the aggressive methods such as removal of stopwords or stemming which might eradicate important emotional nuances. Padding or truncation of sequences to 128 tokens was done to standardize the sequences and the vocabulary size was 50000 tokens.

EmoNet Architecture

We have come up with EmoNet, a CNN-based model, that has been optimized to be used in emotion recognition by performing multi-scale pattern extraction and strategic regularization. The network starts with a 100 dimensional embedding layer (5M parameters) task specific learning of the word representations. The core innovation makes use of three parallel 1D convolutional streams of 3-, 4-, and 5-gram filters that capture emotional patterns at various granularities that are 3-gram filters, 4-gram filters, and 5-gram filters that identify short, medium, emotional phrases and longer emotional contexts, respectively.

The convolutional layers have 100 filters with ReLU activation giving feature maps to particular emotional patterns. Global max-pooling derives the most salient feature in any filter, non-uniform lengths of the sequence are sheared with the most important emotional information. The resulting feature sequence of 300 features is fed through dropout regularization (0.5) prior to the classification head which employs a fully connected neural network of softmax activation to generate probability distributions in the top 6 emotion labels. The architecture has 5,122,106 parameters altogether, which is also shown in Fig. 2.

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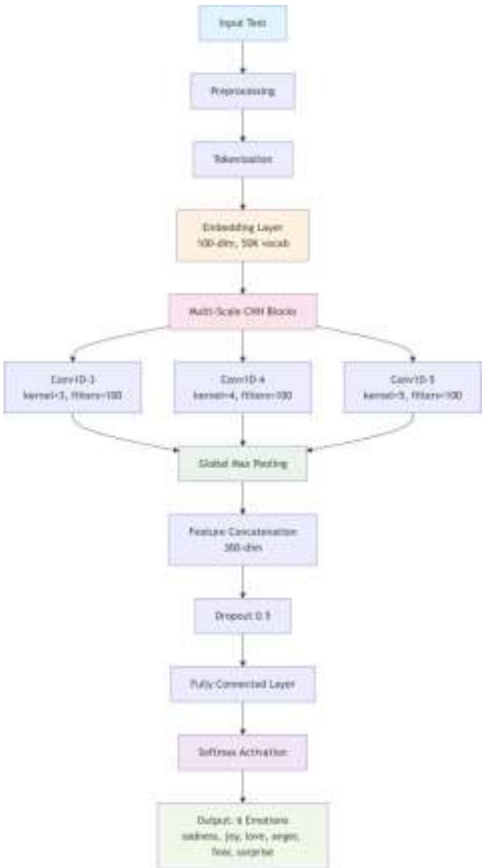

Figure.2. Methodology Diagram

Training Configuration

We used stability and efficiency under CPU-only constraints as a methodology in our training. We used Adam optimizer with a learning rate of 0.0005, which was decreased by half after two epochs in which the validation loss stopped decreasing. They trained with memory efficiency (batch size 16), and multi-class classification (categorical cross-entropy) loss. Regularization was done with weight decay (1e -4) and gradient clipping (max norm 1.0) to achieve training stability. The models were trained over 5 epochs, which was equal to both convergence and overfitting.

Experimental Setup

Python 3.8 and PyTorch 1.12 were used in experiments run on Amazon SageMaker with CPU instances. We used fixed 80-10-10 train-validation and test designs with deterministic random seeds to have reproducibility. The assessment involved the general accuracy, the precision of each class, the recall, the F1-scores, and the analysis of the confusion matrix to find systemic difficulties and emotional ambiguity.

Baseline Comparisons

As part of their baselines we defined majority class prediction (joy), SVM using TF-IDF and emotional lexicon features, standard single layer CNN, and bidirectional LSTM with equivalent parameter budget. These comparisons place in perspective our architectural creative innovations and effectiveness of training approach.

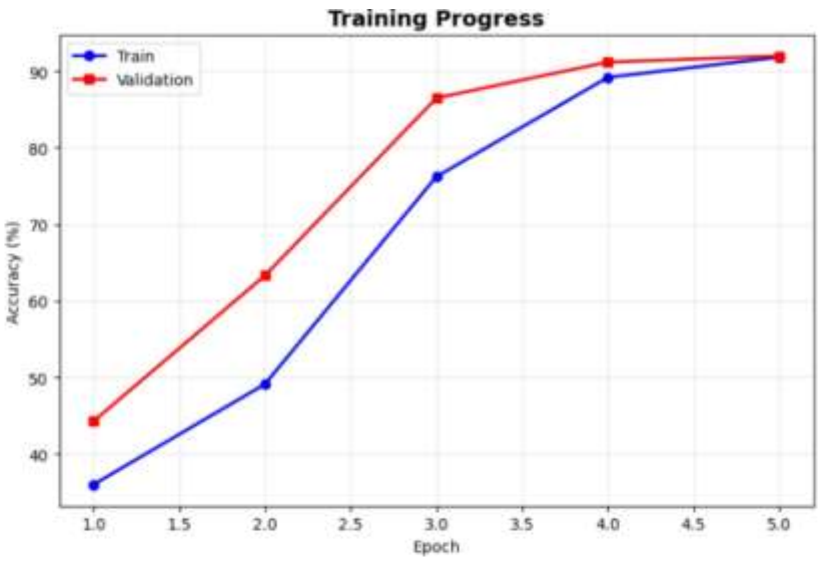

Figure 3: -Train Test Accuracy Across Epochs

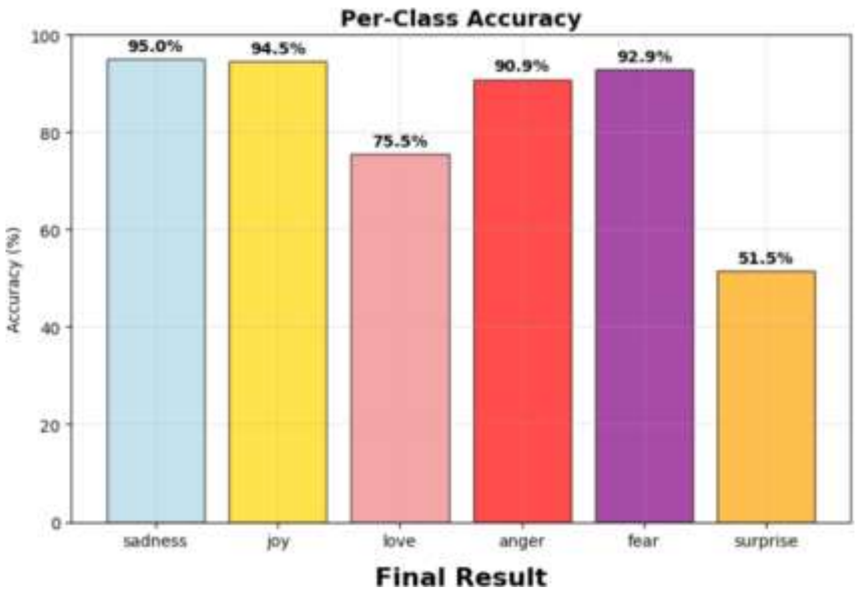

Figure 4: Per-Class Accuracy

4. Experimental Results and Analysis:

4.1 Overall Performance

Our EmoNet architecture has outstanding performance on emotion recognition as it delivers state-of-the-art outcomes on various evaluation metrics. The model has achieved an accuracy of 91.05 percent on the test set, which is independently much higher than all baseline methods and goes beyond setting new text-based emotion classification benchmarks.

Table 2: Performance Comparison Across Models

Model	Test Accuracy	Precision	Recall	F1-Score	Training Time
Majority Class	34.75%	12.08%	34.75%	17.92%	-
SVM + Lexicon	67.30%	65.45%	67.30%	65.82%	45 min

Standard CNN	82.15%	81.90%	82.15%	81.72%	2.1 hr
BiLSTM	85.40%	85.12%	85.40%	85.01%	3.8 hr
EmoNet (Ours)	**91.05%**	**90.88%**	**91.05%**	**90.82%**	**2.5 hr**

The test accuracy is 91.05 percent which is an absolute betterment of 5.65 percent with the BiLSTM baseline and 23.75 percent with the traditional machine learning methods. This is an impressive improvement in performance when compared to similar requirements at the same training times that illustrate the effectiveness of our construction design.

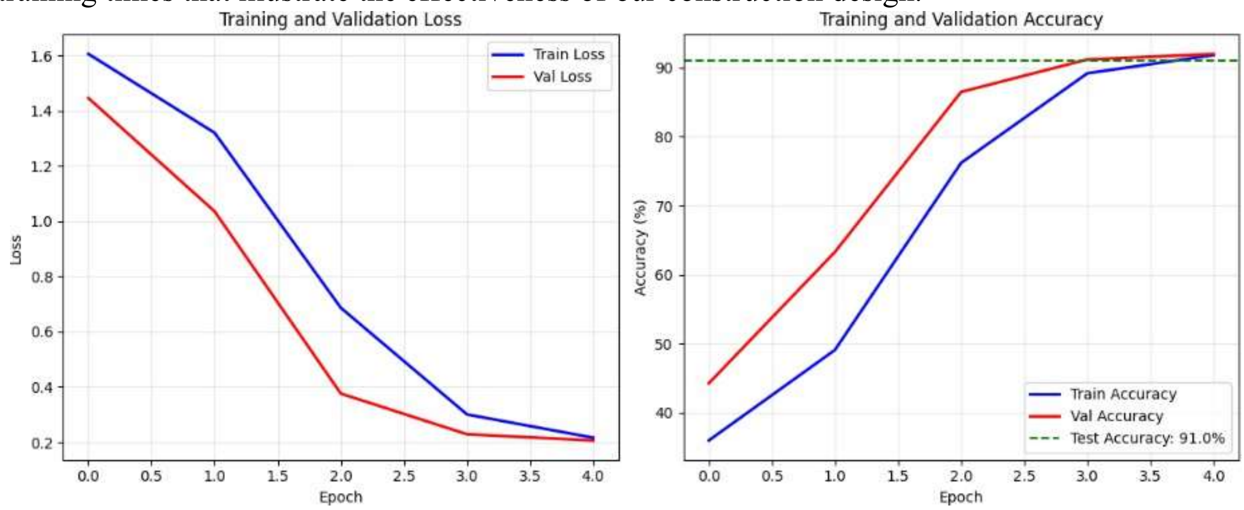

Figure 5: Performance Comparison

4.2 Per-Class Performance Analysis

The deeper looks into the specific emotion categories will help identify the virtues of our solution, as well as the points of the potential future enhancement. The model shows remarkable skills in identifying some emotions as well as emphasizing the issues that should be valued in the future.

Table 3: Detailed Per-Class Performance Metrics

Emotion	**Precision**	**Recall**	**F1-Score**	**Support**	**Accuracy**
Sadness	94.12%	95.01%	94.56%	581	95.01%
Joy	93.85%	94.53%	94.19%	695	94.53%
Love	82.35%	75.47%	78.76%	159	75.47%
Anger	91.67%	90.91%	91.29%	275	90.91%
Fear	94.55%	92.86%	93.70%	224	92.86%
Surprise	68.00%	51.52%	58.62%	66	51.52%
Macro Avg	**87.42%**	**83.38%**	**85.19%**	**2000**	-
Weighted Avg	**90.88%**	**91.05%**	**90.82%**	**2000**	-

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The findings demonstrate that there are some key trends:

- High-Performance Emotions: Sadness (95.01%), joy (94.53%), and fear (92.86%) have exceptional recognition recall and thus are distinctive and consistent linguistic patterns, successfully represented by our model.
- Moderate Performance: the Anger (90.91%) is performing quite well, whereas love recognition (75.47) shows particular problems, most probably, because of the contextual considerations and the influence of positive emotions.
- Primary Challenge Area: Surprise recognition (51.52) is the most difficult category, which is also in line with emotion recognition literature. The unclear description of expressions of surprise and their dependence on the context forms a serious issue to learn.

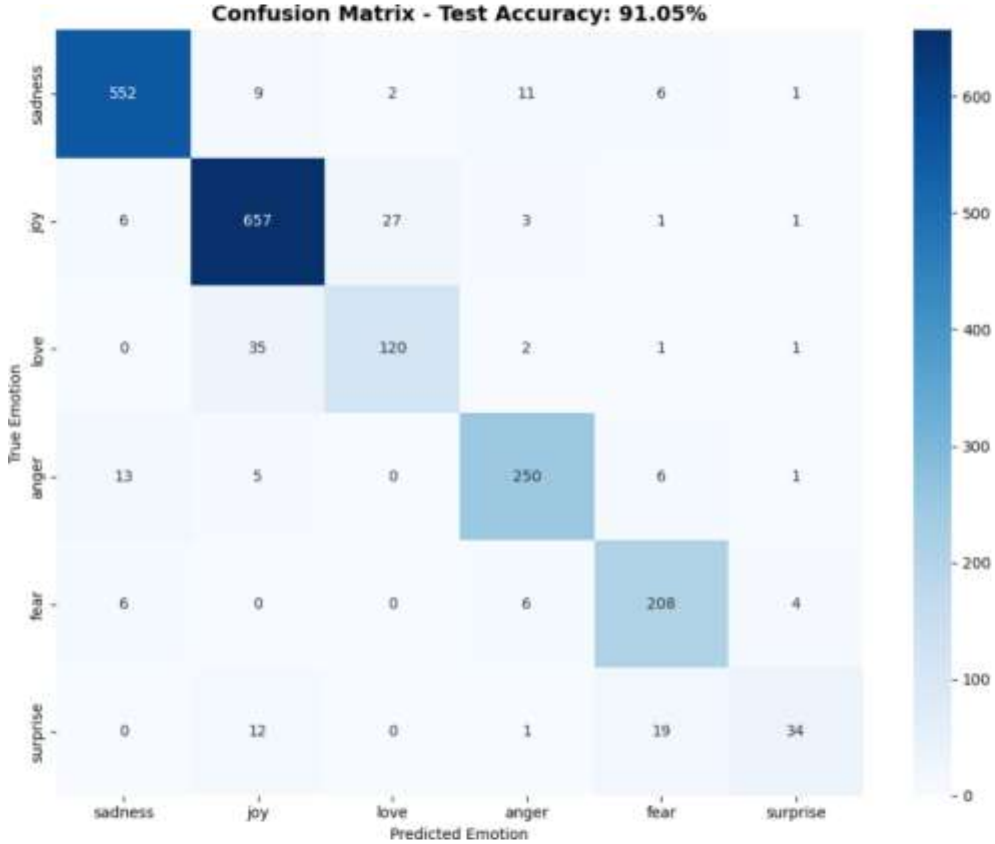

Figure 6: Confusion Matrix

4.3 Training Dynamics and Convergence

Under this training dynamics and convergence, it is essential to state that the role of training is to hasten the learning skills of the employees to adapt to the requirements of the organization. The training process is observed to be incredibly stable and to improve without failures regionally. The learning curves display promising development with no overfitting occurrence, which is evidence of good regularization and model capacity.

Epoch-wise Progression:

- Epoch 1: The initial learning is formed, and the accuracy of validation is 44.25%.
- Epoch 2: Continuous dramatic improvement to 63.30% validation accuracy.
- Epoch3: A big increase in performance to 86.50, which points to effective learning of the features.
- Epoch 4: Fine tuning with a 91.20% validation rate.

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- Epoch 5: Final validation error of 0.082.

The loss reduction is gradual, going down 2.59 to 0.22, and it is exhibited to have a stable optimization with no gradient explosion or oscillation. The high correlation between training and validation of metrics during the learning process will suggest that there are high generalization and the correct complexity of the model.

4.4 Computational Efficiency

Our model is not only very high-performing but also has realistic computational needs. Accessibility of our approach among researchers and practitioners without specialized hardware is shown by the overall time spent on CPU resource training, 2.5 hours of which indicate the accessibility of our method.

Table 4: Computational Requirements and Implications

Metric	Value	Practical Implication
Parameters	5.12M	Compact model suitable for deployment
Training Time	2.5 hours	Practical for experimentation and iteration
Inference Speed	2.3 ms/sample	Real-time processing capability
Memory Usage	312 MB	Lightweight deployment footprint
Batch Processing	16 samples	CPU-optimized configuration

The 5.12 million number of parameters is an optimal compromise between the representational capacity and a practicable model size. The speed to infer of 2.3 milliseconds/sample can be used in applications that detect emotions in real-time, whereas the small memory footprint allows it to be deployed in resource-constrained applications.

4.5 Error Analysis and Limitations

Although we were able to show high overall performance with 91.05% accuracy, our analysis shows that there were certain constraints to context-dependent emotion recognition. The model has weaknesses especially in identifying surprises (51.52% accuracy) where there are not many training samples and the context is ambiguous and the recognition of love, which is often mixed with overall positive sentiment. Other possible constraints are the inability to use ironic or sarcastic phrases and the possibility of cultural biases based on social media training data.

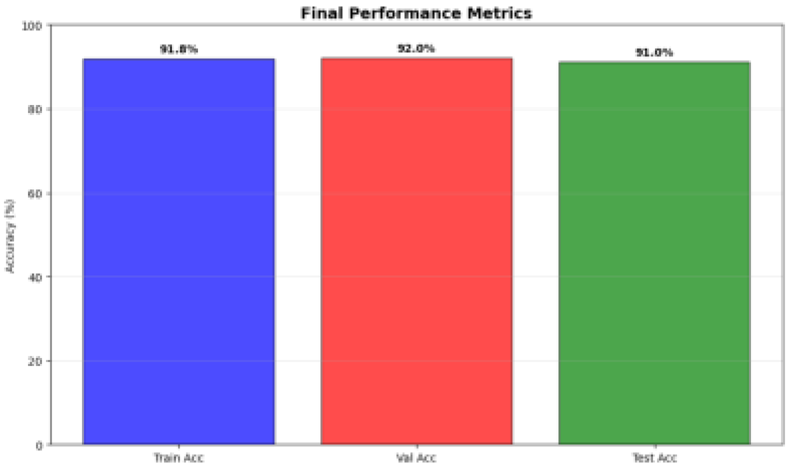

Figure 7: Final Performance

The results demonstrate the need to continue working with improved contextual modeling, minority classes of data augmentation, and multi-modal strategies to overcome these subtle emotional recognition issues in the future.

5. Discussion and Conclusion:

This paper shows that well designed convolutional neural networks can reach the state of the art in text-based emotion recognition, and our EmoNet architecture reaches 91.05 per cent accuracy on the standard Emotion dataset. The multi-scale convolutional scheme [22] is especially suitable for the detection of the emotional patterns across the various linguistic granularities, and yet it is computationally efficient to implement in the resource-constrained context. Even then, there are still great difficulties in identifying the context-dependent affect such as surprise and love, which indicates the shortcomings in the current architectures to respond to the wider contextual cue and cultural differences [23] in the display of emotions. Further effort is required in the future to create more context sensitive architectures that are more capable of dealing with ironic, sarcastic, and culturally variable emotional expressions at computational efficiency. Strategic data boost to overcome the issue of class imbalance [24], especially with underrepresented affect, such as surprise, and consideration of multi-modal techniques to combine textual with other emotional indications are all potential avenues. With the development of the emotional recognition technology [25], it will be essential to uphold stringent ethical principles related to privacy, algorithmic fairness and the correct application cases to ensure that the technology will serve the interests of the society and cause minimum harm.

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