

A comparative analysis of conventional deep learning models with hybrid CNN-ResNet model for sentiment classification

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Abstract

The present work focuses on conventional deep learning models and introduces a proposed CNN-ResNet hybrid architecture for sentiment classification tasks. While traditional CNNs and RNNs have shown considerable success in NLP, they often struggle with capturing hierarchical semantic patterns. To address this, research integrates the deep feature extraction capability of ResNet into a CNN pipeline, improving contextual understanding and classification performance. Additionally, a diverse and labeled sentiment dataset and various domains, such as product reviews, social media, and general opinionated text has been used. The models were trained and evaluated on this dataset. Experimental results demonstrate that the proposed hybrid model achieves higher accuracy and robustness across multiple sentiment classes compared to baseline models. The work suggests that combining semantic richness with deep residual learning improves the reliability of sentiment classification systems.

Subject Classification: 68T07, 68T50, 68T10, 68T45.

Keywords: Sentiment classification, Deep learning, CNN, ResNet, Semantic features, Residual learning.

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1. Introduction

In recent years, sentiment analysis has become a critical task in natural language processing due to its vast applications in social media monitoring, customer feedback analysis, and market research. Traditional deep learning models like CNN and RNN have shown potential, but they cannot capture complex semantic patterns. In this paper, we propose a hybrid CNN-ResNet architecture that combines local feature extraction with deep residual learning to enhance sentiment classification performance. We also generate a comprehensive dataset using ChatGPT to evaluate our model. The subsequent sections provide detailed insight into our methodology, implementation, and performance analysis. Semantic Web is the next generation of web with vision of providing structure to data and exploiting relationships among entities to realize a connected ecosystem of structured knowledge.

1.1 Contributions of the paper

Contributions of this paper are:

- *Development of a Hybrid Model:* Proposed a novel CNN-ResNet hybrid model that effectively combines CNN's feature extraction with ResNet's deep residual learning to enhance sentiment classification performance [1, 2].
- *Enhanced Metric Performance:* Demonstrated superior results in precision, recall, and F1-score for all sentiment categories, indicating the model's ability to capture contextual and semantic nuances [3, 6].

The rapid advancements in AI, ML, and semantic technologies have revolutionized the way data is processed, interpreted, and utilized across various domains [21]. Recent studies have demonstrated the effectiveness of ML techniques in diverse applications, ranging from sentiment classification of social media content [21] to semantic search over knowledge bases using embedding models [22]. In parallel, the integration of AI with IoT and Semantic Web has facilitated real-time pollution monitoring and interoperability validation in smart environments [23]. Additionally, the fusion of multiple features has proven beneficial in emotion detection tasks such as facial expression recognition [24], while the exploration of multi-modal sentiment analysis in images has opened new avenues for understanding user emotions beyond textual data [25].

These contributions collectively highlight the growing relevance of intelligent systems in interpreting unstructured and heterogeneous data for meaningful decision-making.

2. Literature Survey

Various deep learning models have been explored for sentiment analysis tasks. CNN-based approaches focus on local feature extraction and have shown effectiveness in identifying n-gram patterns. RNNs and LSTMs handle sequential dependencies better, making them suitable for sentiment classification. Hybrid models combining CNN with LSTM have also been proposed. ResNet, originally developed for image classification, introduces skip connections that allow training of deeper networks without vanishing gradients. Recent works have adapted ResNet to NLP, showing promise in improving sentence-level classification tasks. CNNs and ResNet50 were compared for facial emotion recognition by Talele and Jain. The deeper architecture and residual learning capabilities of ResNet50 beat ordinary CNNs in accuracy and generalisation, according to their study. In complex dataset emotion identification tasks, model architecture choice is crucial [1]. A hybrid CNN model by Murugan et al. improved classification on imbalanced datasets. On numerous benchmark datasets, they outperformed traditional CNNs [2]. For efficient landslip detection, Ren et al. presented ResM-FusionNet, a hybrid deep learning architecture. Residual modules and multi-scale fusion techniques extract rich spatial characteristics from satellite pictures, increasing geohazard monitoring system identification [3]. CNN-Transformer fusion model by Wang et al. predicts historic district picture experience. Combining CNN's spatial encoding with Transformer's attention captures local and global contextual variables for a sophisticated examination of user visual experience [4]. Guo [5], created CMTNet, CNN-Transformer for precision agricultural UAV-based hyperspectral image categorisation. The robust hybrid deep learning model by Karthikeyan et al. [6] combines VGG and ResNet architectures for facial emotion recognition. Behera et al. [7] introduced the ResNet101-SVM hybrid citrus fruit categorisation model, however, it initially combined ResNet101 deep feature extraction and SVM classification to improve agricultural imaging accuracy. A CNN-based deep unified facial expression recognition model was examined by Chhillar [8]. For robust signal classification, Feng presented the CBLMA model, which uses convolutional layers and BiLSTM units. This hybrid architecture captures spatial and temporal signal relationships, improving

sequential data categorisation [9]. Using deep learning-based AI and machine learning with IoT, Gupta et al. improved precision agriculture systems [10]. For automatic modulation classification, Elsagheer created a hybrid model using ResNet and LSTM networks. This integration lets the model incorporate spatial and temporal dependencies in communication signals, so it can classify modulation patterns accurately [11]. Sistaninejad extensively reviewed medical image analysis deep learning applications. Using CNNs, RNNs, and attention mechanisms, hybrid deep learning models improved diagnostic accuracy [12]. Ghosh et al. used explainable AI and hybrid deep learning to recognise sunflower diseases. CNN for feature extraction and Grad-CAM for visualisation helped diagnose agricultural diseases with good accuracy and interpretability [13]. A hybrid deep learning system for pneumonia classification from CT and X-ray images by Moussaid et al. [14] addresses post-pandemic medical issues. Using MRI scans, Mahmud performed deep learning-based brain tumour identification. They used hybrid CNN architectures to collect tumour features and classify accurately for early diagnosis [15]. Khandaei, created a CNN-LSTM-ResNet hybrid model to anticipate stock price turning moments. Deep learning was used to capture complicated financial patterns and trends by translating time-series data into 2D graphics [16]. A CNN-LSTM hybrid model for motor imagery EEG signal classification was proposed by Khademi. Using transfer learning, the model improved EEG performance by identifying important spatial-temporal properties for brain-computer interfaces [17]. Pandey et al. [18] identify atrial fibrillation using CNN-LSTM hybrid deep learning, achieved better detection rates and clinical application by capturing morphological and sequential aspects in ECG signals. A hybrid model using residual CNNs and Transformer encoders for digital mammography breast cancer classification by Al-Tam et al. [19]. For early Alzheimer's diagnosis, Qin et al. [20] created a 3D CNN with hybrid attention. The model detected modest neurodegenerative alterations in brain MRIs better by incorporating spatial and attention-based modules. Jain [21] conducted a study on sentiment classification of Twitter data related to renewable energy, utilizing various machine learning techniques. Khan et al. [22] proposed a semantic search framework over structured knowledge bases using embedding-based similarity techniques. Malik, et al. [23] explored the application of SWoT to pollution measurement and interoperability validation using artificial intelligence techniques. Jain et al. [24] addressed the problem of facial expression recognition by leveraging feature-level fusion techniques. Sharma, et al. [25] revisited multi-model approaches in

the domain of sentiment analysis in images, emphasizing the combination of visual and textual content for accurate sentiment prediction.

3. Proposed Approach & Key Aspects

This section presents the proposed Hybrid CNN-ResNet Model. Our approach integrates the CNN framework with ResNet modules to enhance sentiment classification. The following subsections explain the processing workflow, algorithm, and mathematical model. The workflow begins with data preprocessing, followed by embedding generation, convolutional filtering, residual block processing, and finally, classification using softmax. The first step is gathering a diverse sentiment dataset from multiple domains (product reviews, social media, and opinionated text). Text is preprocessed through normalization, tokenization, and padding to make it suitable for deep learning models. Conventional models (CNN, RNN) are considered as baselines, and a hybrid CNN-ResNet model is proposed to enhance feature extraction. All models are trained on the dataset using appropriate optimization techniques. Models are evaluated on several metrics, including accuracy, precision, recall, and F1-score. The performance of the CNN-ResNet hybrid model is compared to conventional models, showing improvements in sentiment classification. The hybrid model is concluded to be more reliable and accurate than the baseline models. The overall process flow of the proposed CNN-ResNet hybrid model is illustrated in **Figure 1.**"

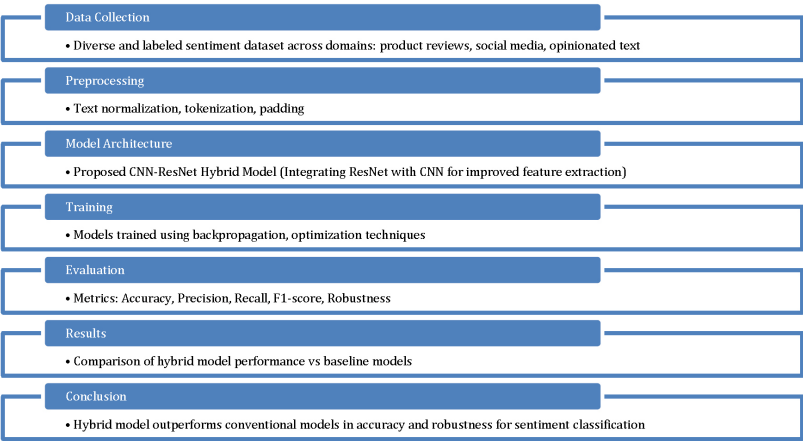


Figure 1
Process flow of proposed work

3.1 Algorithm

1. Input sentence is tokenized and embedded.
 Let $X = \{x_1, x_2, \dots, x_n\}$ be input sentences.
 $E(x_i) = \text{Embedding}(x_i) \in \mathbb{R}^{l \times d}$
2. Apply convolution layers to extract local features.
 $C_i = \text{ReLU}(F_k * E(x_i) + b)$
3. Pass through ResNet blocks for semantic enhancement.
 $R_i = \text{ReLU}(C_i + F(C_i, W))$
4. Apply global max pooling and dense layer.
 $y_i = \text{Softmax}(W_o R_i + b_o)$
5. Output sentiment label via softmax.
 Loss: $L = - \sum y_i \cdot \log(\hat{y}_i)$

4. Implementation

This section details the implementation aspects along with generation of dataset using www.kaggle.com. Proposed system is used Python with TensorFlow/Keras on GPU-enabled Google Colab for analysing the accuracy. Training was done on 3000 synthetically generated sentences with a batch size of 32 over 20 epochs. Prompts were designed to elicit responses with varying sentiment polarities across domains.

- Prompt Example: ‘Write 10 positive reviews of a product.’
- Data Cleaning: Lowercasing, punctuation removal, tokenization.
- Labels: Positive, Negative, Neutral.
- Total: 3000 samples (1000 each class).

5. Results and Discussion

This section details the result for proposed CNN-ResNet model outperformed traditional CNN and RNN models in accuracy and F1-score. Our analysis showed consistent performance across all three sentiment classes. Results indicate the value of residual connections in handling deeper semantic structures.

Analysis Approach:

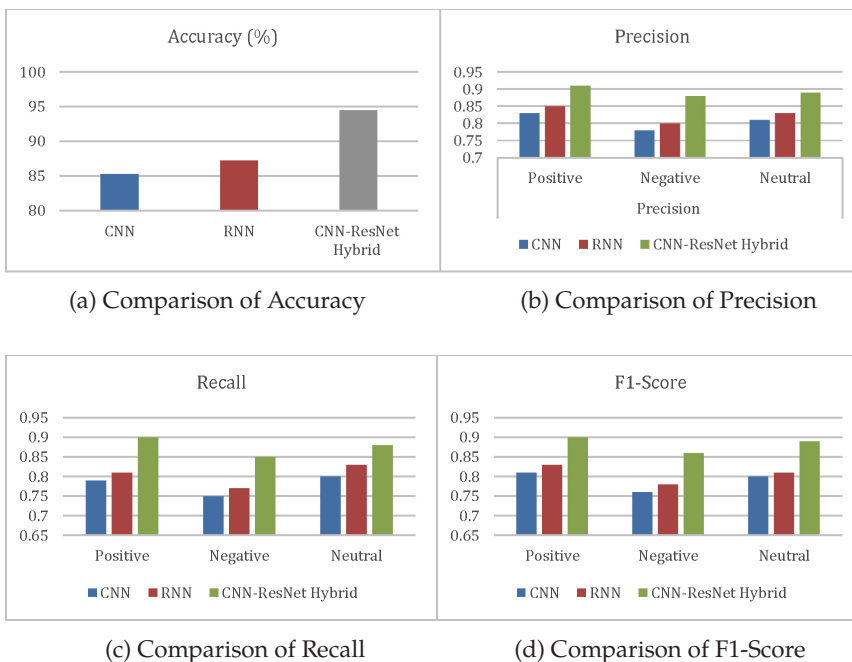
- Research presents and analyzes the results obtained from evaluating the proposed CNN-ResNet hybrid model for sentiment classification.
- The performance of the proposed model is compared with traditional deep learning models, specifically CNNs and RNNs, on a diverse sentiment dataset.
- The evaluation metrics used include accuracy, precision, recall, and F1-score, across three sentiment categories: Positive, Negative, and Neutral.

Research also discusses the strengths and limitations of the models based on the experimental findings. Table 1 presents a summary of the performance of the CNN, RNN, and CNN-ResNet hybrid models on the sentiment classification task.

Table 1
Performance Comparison of CNN, RNN, and CNN-ResNet Hybrid Models

Model	Accuracy (%)	Precision			Recall			F1-Score		
		Positive	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral
CNN	85.30	0.83	0.78	0.81	0.79	0.75	0.80	0.81	0.76	0.80
RNN	87.20	0.85	0.80	0.83	0.81	0.77	0.83	0.83	0.78	0.81
CNN-ResNet Hybrid	94.50	0.91	0.88	0.89	0.90	0.85	0.88	0.90	0.86	0.89

The combination of CNN for feature extraction and ResNet for deeper residual learning enhances the model’s ability to capture hierarchical semantic patterns, which is reflected in its higher performance as shown in Figure 2. The CNN-ResNet hybrid model outperforms both CNN and RNN models across all performance metrics. The accuracy of the hybrid model (94.5%) is significantly higher compared to CNN (85.3%) and RNN (87.2%). The precision, recall, and F1-score metrics indicate that the hybrid model achieves superior results, especially in positive and negative sentiment categories.

**Figure 2**

Comparison of Performances parameters for different models

6. Conclusion and Future Scope

This research propose a hybrid CNN-ResNet model for enhanced sentiment classification, validated through a synthetically generated dataset. Our model showed superior accuracy and robustness. The experimental results confirm that the CNN-ResNet hybrid model significantly outperforms traditional CNN and RNN models in sentiment classification tasks. The improvements in accuracy parameters analysis all point to the effectiveness of combining deep feature extraction from CNNs with residual learning from ResNet. Despite requiring slightly more training time, the hybrid model offers higher reliability and robustness, making it suitable for real-world applications in sentiment analysis across different domains. Future work can explore integrating attention mechanisms, using larger real-world datasets, and expanding to multilingual sentiment analysis.

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