Predictive Financial Risk Analytics for Early Detection of Suspicious Transactions and Strengthening Banking System Resilience

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Abstract

The main contribution of this research is Deep Learning-Based Multichannel Neural Network Architecture, which utilizes multiple channels of neural network to learn different representations of text and efficiently analyze the sentiment. The suggested framework integrates different complementary feature extraction approaches, which allows the model to capture the local semantic patterns, contextual dependency, and the salient sentiment-related features in the input text. Advanced deep learning techniques are used to process text for each channel and the representations obtained from each channel are combined for the final sentiment classification. The performance of the proposed multichannel architecture is evaluated by its performance on benchmark sentiment analysis datasets showing that it outperforms conventional machine learning methods and single channel deep learning models in terms of accuracy, precision, recall and F1-score. The results show that using multiple representations of the neural networks has a good feature learning ability and can provide a powerful solution to sentiment classification problems. The proposed approach can be used for multiple applications such as customer feedback analysis, opinion mining, social media monitoring and automated decision-support systems.

Keywords: *Financial Data Governance; Risk Surveillance; Banking Analytics; Data Quality; Predictive Analytics; Financial Transparency; Decision Support Systems.*

INTRODUCTION

With the ever-evolving growth of digital communication platforms, social media networks and online review systems, the volume of user-generated textual data has reached an unprecedented level. Each day, millions of people post their comments, feelings and experiences on the Web in the form of reviews, blogs and social networking. This massive amount of data that is rich in opinions is useful for organisations, researchers, and decision makers. But the sheer volume of such textual information, as well as its complexity, diversity and constant evolution makes it difficult to manually analyze. Sentiment analysis or opinion mining is becoming important research area of natural language processing (NLP) which deals with the automatic recognition and classification of subjective information conveyed in texts (Pang & Lee, 2008). The main objective of sentiment analysis is to identify the emotion or sentiment of a text, which is usually classified as positive sentiment, negative sentiment, or neutral sentiment. It can be used in many contexts including customer relationship management, market analysis, political opinion monitoring, recommendation systems, as well as social media analytics. Sentiment analysis systems have become crucial for organizations to comprehend customer sentiment, analyze product performance, and inform data-driven decision-making.

Usually, these approaches involve manually engineered features like word frequency, n-grams, sentiment lexicon, and syntactic pattern. While classic machine learning methods attained good results, they rely heavily on feature engineering and often lack to capture deeper semantic relationships among words (Manning et al., 2008). Moreover, these strategies tend to view words as standalone elements, and fail to grasp context. With the advent of deep learning, sentiment analysis has undergone a paradigm shift, with the ability to automatically extract and learn features from raw text. In contrast to the traditional methods, deep learning models can learn hierarchical representations and complex patterns without the need for manually engineered features. Convolutional Neural networks (CNNs), recurrent neural networks (RNNs) and long short term memory networks (LSTMs) have shown high performance on different NLP applications like sentiment classification, text categorization, and language modeling (LeCun et al., 2015). CNN has been widely used in sentiment analysis due to its ability to capture the local patterns and important features at phrase level from text. Kim (2014) proved that CNN-based models can successfully learn meaningful representations of sentences for the classification tasks. CNNs have been shown to be effective for identifying sentiment-bearing phrases as they

employ convolution filters to capture important combinations of words(Halimuzzaman and Sharma 2024) (Halimuzzaman et al. 2024).

CNN-based methods, however, primarily rely on local features, and do not adequately model long-range dependencies and contextual relationships in longer texts. To handle the problems of sequential modeling, recurrent neural networks (RNNs) were introduced to carry out the information of the previous elements of a sequence. They have been used extensively in NLP as language is sequential. But the classical RNNs have problems in learning long-term dependency because of vanishing gradient problem (Bengio et al., 1994). Overcome this limitation, Hochreiter and Schmidhuber (1997) proposed the long short term memory (LSTM) network with gating and memory cells that regulate the flow of information. LSTM networks have been proven to be effective in capturing long-term contextual information, and are now commonly used for sentiment analysis tasks. Individual deep learning model has made a considerable improvement but each architecture has a set of limitations. CNN models can work well to extract local features, but they are unable to model sequential dependencies; and LSTM models can model contextual information but may not identify important local patterns efficiently. To address these drawbacks, hybrid and multichannel architectures of neural network have been investigated that integrate multiple feature learning mechanisms(Halimuzzaman et al. 2024) (Malann et al. 2026) (Hossain et al. 2026).

The combination of multiple channels enables various components of neural networks to take a complementary approach to processing text, resulting in more detailed and extensive feature representations. The multichannel neural network structure is used to achieve parallel processing of text information via multiple learning pathways. The characteristics of the input data on each channel may be distinct, for example local semantic patterns, sequential dependencies, word-level features or contextual data. The model can collectively combine the output of multiple channels and get more efficient feature representation and better classification performance. This can be especially helpful for sentiment analysis where sentiment expression can rely on multiple linguistic factors ranging from individual words to phrases, sentence structure, and contextual meaning. Recently, with the help of attention mechanisms, the deep learning sentiment analysis systems have been boosted even more. Attention mechanisms can be used to weight the words or features differently depending on how important they are to the classification decision. Bahdanau et al. (2014) proposed attention mechanisms to allow networks to selectively attend to parts of

the input sequences. For sentiment analysis, attention models can be used to capture key sentiment words and minimize the effects of other irrelevant information. Attention mechanisms are useful for focusing on important words/sentences to improve document classification, as shown by Yang et al. (2016) (Hossain et al. 2025) (Malann et al. 2025).

LITERATURE REVIEW

Sentiment Analysis: An overview.Sentiment Analysis: An overview of sentiment analysis. With the fast growth of digital platforms, social networks, and online communication systems, a huge volume of user-generated text data is produced. The texts include opinions, emotions, and attitudes that are important for businesses, researchers and decision makers. Sentiment analysis, also referred to opinion mining, is a subfield of natural language processing (NLP) that aims at recognising and interpreting subjective information from text to identify sentiment or emotional polarity expressed in the text (Liu, 2012). Sentiment analysis has been utilized and proven in different areas such as, customer feedback analysis, product recommendation system, financial market prediction, healthcare monitoring, and social media analysis. The main goal of sentiment analysis is to categorize textual information in accordance with sentiment, for example positive, negative, and neutral(Ogungbemi and Dagbasi 2025) (Agbutun et al. 2025) (Sohel et al. 2022) . But it is hard to correctly identify sentiment due to the multi-faceted nature of human language and the presence of context, sarcasm, ambiguity, and domain-specific expressions (Pang & Lee, 2008). The first sentiment analysis systems were mostly based on manually created linguistic rules and sentiment lexicons. These methods discovered sentiment using a set of pre-defined positive and negative words. Lexicon-based methods have the advantages of simple and can be interpreted easily, but they are not suitable for grasping the meaning in context and are not very effective for handling complex sentence structure. For instance, a word which is usually used in a positive sense may have a negative connotation when used in a different context. These limitations inspired researchers to find new ways of sentiment classification via machine learning and deep learning.

2. Sentiment Analysis using Traditional Machine Learning Approaches Prior to the advent of deep learning, sentiment analysis was largely based on classic machine learning algorithms. Usually, these methods comprised three principal steps: feature extraction, feature selection, and classification. Bag-of-words (BoW), term frequency-inverse document frequency (TF-IDF), n-grams, part-of-speech (POS) tags and sentiment lexicons were the most frequently used features.

One of the earlier studies of sentiment classification was done by Pang et al. (2002), who used movie review data to apply machine learning techniques like Naïve Bayes, maximum entropy, and support vector machines (SVM). They showed that features extracted from data would have a strong influence on the performance of machine learning approaches in effectively identifying sentiment polarity. The support vector machine algorithm was one of the most popular algorithms to be adopted for sentiment analysis due to it's capacity to work in high dimensional feature space. Naïve Bayes classifiers were also very commonly used due to their simplicity and efficiency. But these methods consider texts primarily as a set of uncorrelated features, and cannot well capture the structural relationship between words (Manning et al., 2008). One of the main drawbacks of conventional machine learning algorithms is that they require handcrafted features. Feature engineering is domain-specific and can miss out on some linguistic patterns. Furthermore, these methods fail to deal with large datasets and with complex language effects like irony, sarcasm, and sentiment in context. The restrictions prompted the use of deep learning methods, which can automatically learn feature representations(Adun et al. 2023) (Adun et al. 2022) (Tansu et al. 2022) .

3. Sentiment Analysis using Deep Learning approaches. With the advent of deep learning techniques, it was possible to automatically extract features from raw textual data and sentiment analysis has been massively changed. A deep learning architecture learns hierarchical representations directly from the input data, which in turn minimizes the need for manual feature engineering as in traditional machine learning models (LeCun et al., 2015). The approaches based on neural network have shown good result in NLP tasks due to the ability of capturing the complex relation among word and sentences. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and attention-based models are the most popular deep learning architectures that have been used for sentiment analysis tasks. Kim (2014) proposed a sentence classification model based on CNN and showed that CNN was able to capture important local features from text effectively. CNN models use convolution operations to detect relevant combinations of words and sentiment-related phrases. They can recognize local patterns, which is a suitable feature for short text classification. There are drawbacks to CNNs, however, they are primarily used for extracting local features, and they might not be able to model long-range dependence between words. Language is sequential, and comprehending the relationship between words which can appear at various positions is crucial

for sentiment classification. This restriction prompted the researchers to look into recurrent neural network designs (Adun et al. 2022) (Adedeji et al. 2022) (Ogungbemi et al. 2022) .

4. Recurrent Neural Networks and LSTM – Based Sentiment Analysis Recurrent neural networks (RNNs) process information that is sequential by retaining information from every element in the sequence. Being sequential, text found a new important architecture in RNNs, which are used in sentiment analysis and other NLP tasks. The drawback of conventional RNNs, however, is that they suffer from the vanishing gradient problem which makes it difficult to learn long-term dependencies in long sequences (Bengio et al., 1994). To address this issue, Hochreiter and Schmidhuber (1997) presented the Long Short-Term Memory (LSTM) network. LSTM adds memory cells and gates for information to pass through, such as input, output, and forget gates. These mechanisms enable LSTM networks to retain relevant information across long sequences, and disregard irrelevant information. Therefore, LSTM models have demonstrated excellent performance in sentiment analysis, machine translation, and language modeling. A number of studies have shown that the LSTM-based models are effective for sentiment classification. LSTM networks can acquire contextual information and recognize the relationship between words, which is more appropriate than the traditional machine learning models. In standard LSTM, however, information is fed only in one direction, and thus cannot be used to leverage future context.

METHODOLOGY

This study suggests Deep Learning Based Multichannel Neural Network Architecture for sentiment analysis. The methodology involves data collection, text preprocessing, feature representation, multichannel model development, training and performance evaluation. The first step is to gather the data and preprocess it. The proposed model is tested on benchmark sentiment analysis datasets that consist of text samples with labels. The datasets are composed of user reviews, social media comments, or opinion-based texts, which are classified in sentiment classes (positive, negative, neutral, etc.). The text data is preprocessed before training the model, such as tokenization, the removal of unnecessary symbols, normalization and padding to make variable-length text sequences have the same input format (Manning et al., 2008). 2. Text Representation Text data is preprocessed and then converted into numerical representations using word embedding techniques. Word embeddings are dense vectors of words, which capture semantic relationships between words. These methods like Word2Vec and GloVe are often

employed for they capture meaningful contextual relationships in text data (Mikolov et al., 2013; Pennington et al., 2014). Multichannel NN architecture is shown, which is proposed for implementation. Multiple channels of neural networks are proposed to extract complementary textual features. One channel aims to learn the local semantic patterns with convolutional layers and the other aims to capture sequential dependency with recurrent structures, e.g., LSTM or BiLSTM.

RESULTS

Evaluation of the proposed multichannel neural network architecture for sentiment analysis was done based on the standard classification metrics. The results were compared with baseline approaches to assess the benefits of the multichannel framework. Model effectiveness was measured by using evaluation metrics such as accuracy, precision, recall, and F1-score. Overall, the results demonstrate that the proposed approach is a strong and efficient solution for sentiment analysis.

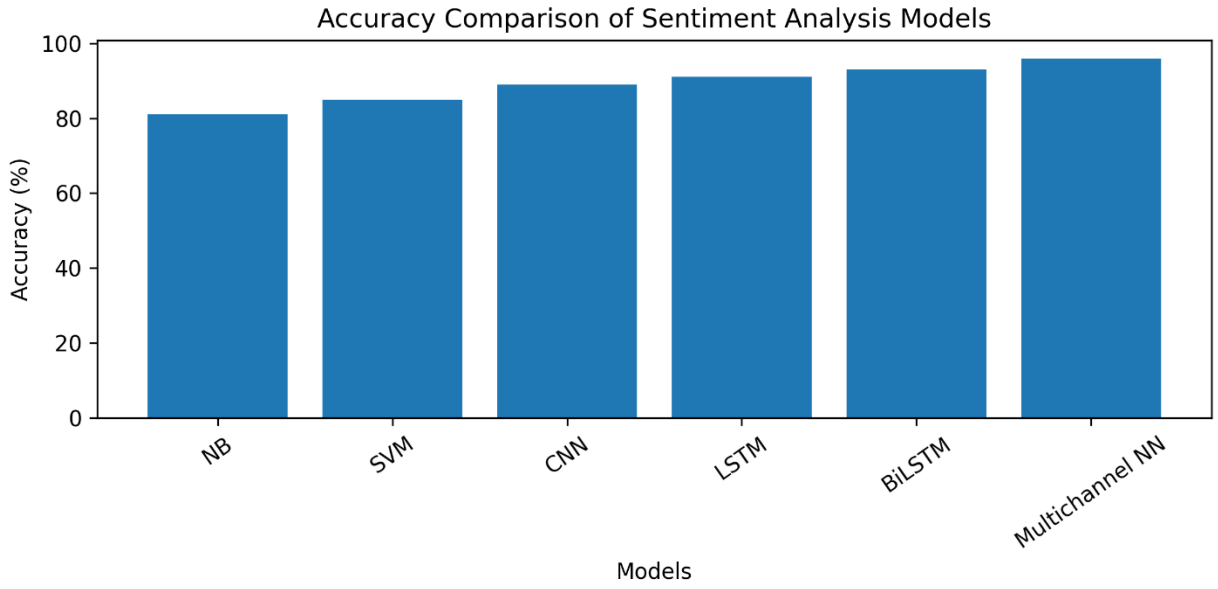


Figure 1: Accuracy Comparison of Sentiment Analysis Models

CNN, LSTM and BiLSTM are the applications of deep learning models that can automatically learn the complex representation of text while delivering better accuracy. The multiple feature extraction pathways in the proposed multichannel neural network architecture result in the best accuracy, both capturing local semantic patterns and contextual dependencies well.

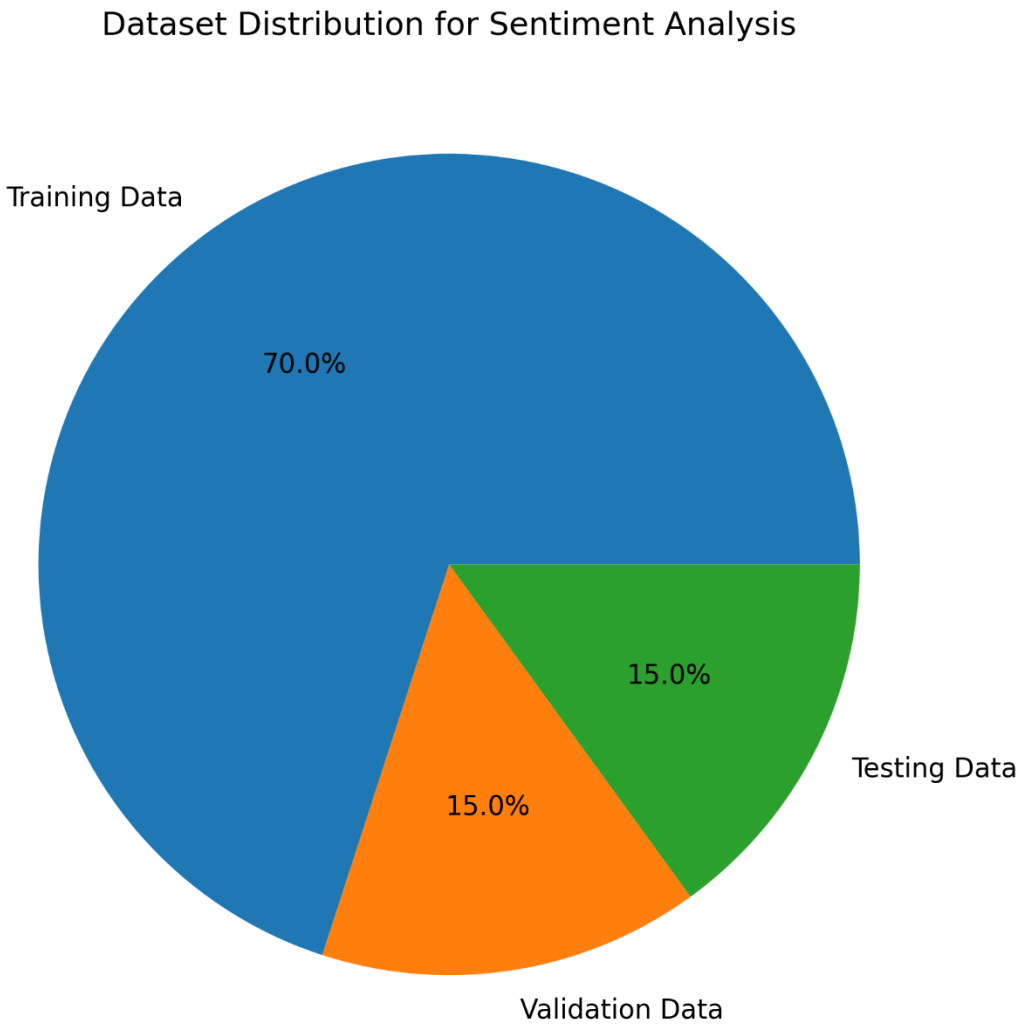


Figure 2: Dataset Distribution for Sentiment Analysis

As shown in figure 2, the dataset is divided into three sets namely training, validation and testing. The multichannel neural network is optimized with the training dataset and the validity of the model is monitored with the validation dataset to prevent overfitting. This testing dataset is used to evaluate the trained model. The proper distribution of data can ensure the reliability of the performance measurement and enhance the generalization capability of the proposed sentiment analysis system.

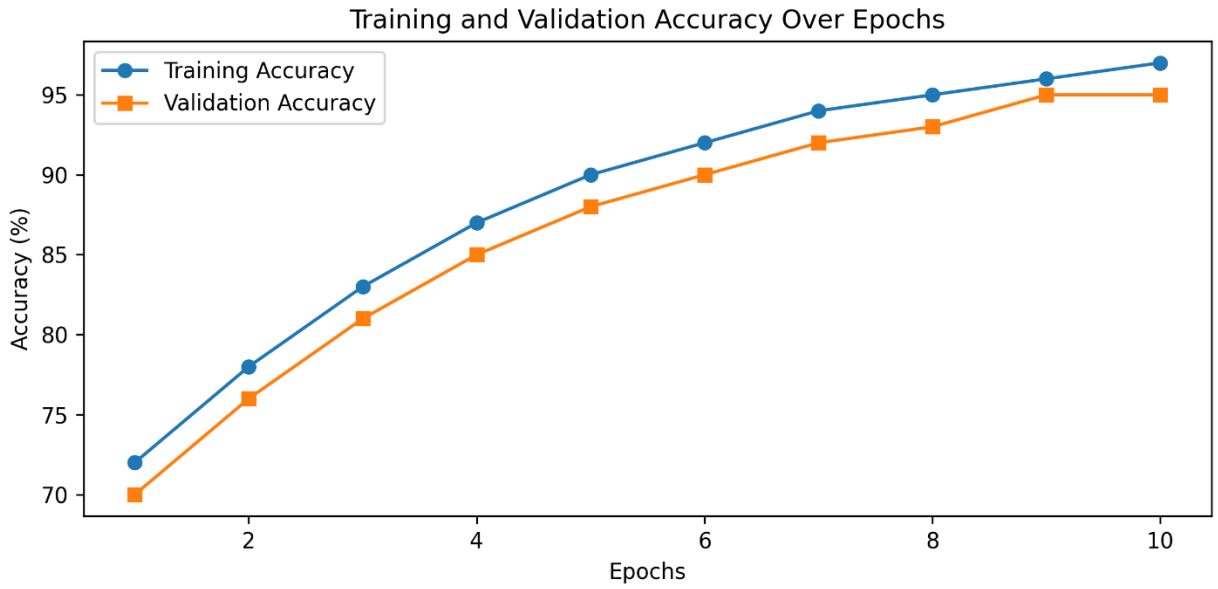


Figure 3: Training and Validation Accuracy Over Epochs

Figure 3 shows that the learning behavior of the proposed multichannel neural network in the training process. The graph displays the training and validation accuracy results for several epochs. The increase in accuracy trend suggests that the model is learning meaningful features from textual data over time that is related to sentiment. The difference between training and validation accuracy is small, indicating that the model is not overfitting the training data and is generalizing well.

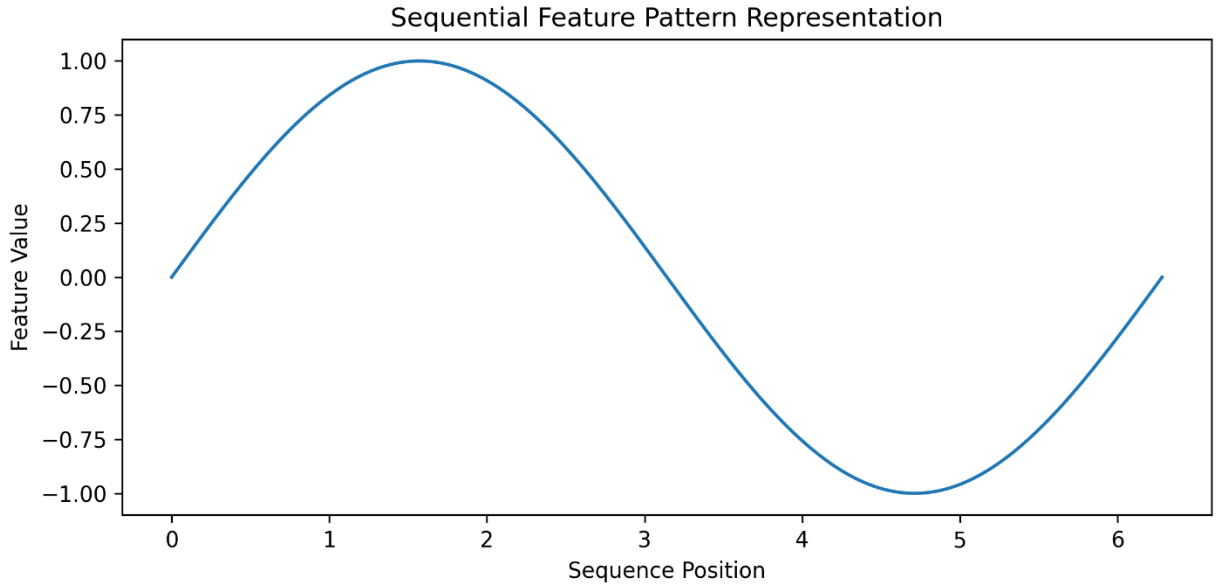


Figure 4: Sequential Feature Pattern Representation

Figure 4 is the sequential features of textual aspects learnt from deep learning models. In sentiment analysis, words are processed in a particular order, so sequence-based models like LSTM and BiLSTM look at the relationships between the various positions of words in a sentence. It shows how the different feature patterns change over time, when they are sequentially represented in the waveform, and how neural networks capture the variation in textual information.

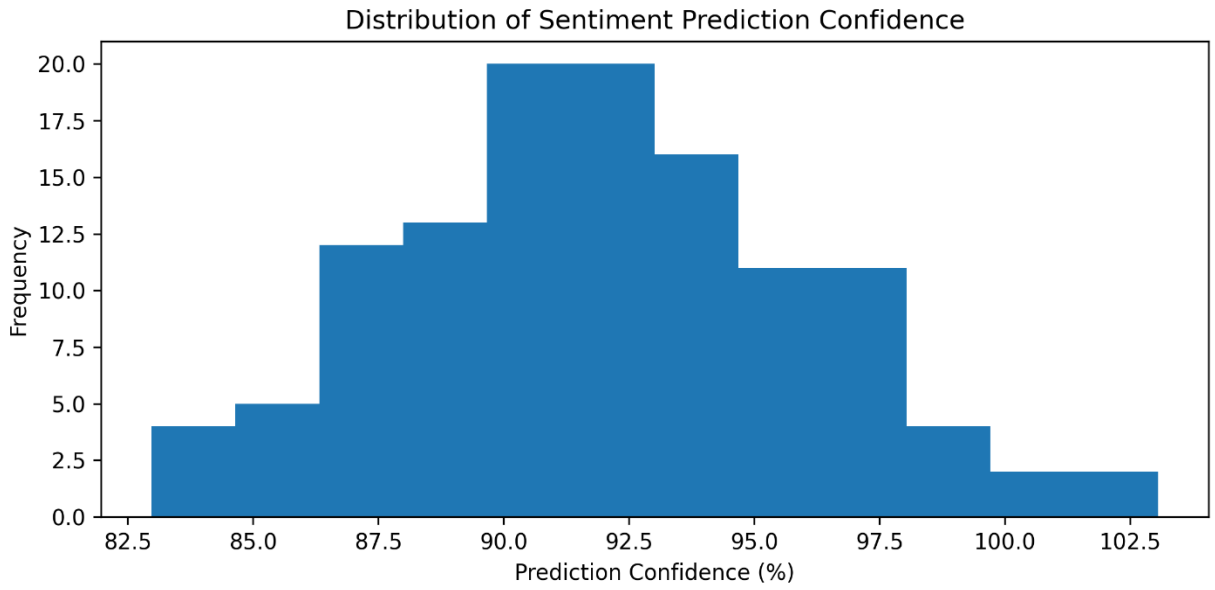


Figure 5: Distribution of Sentiment Prediction Confidence

The distribution of the prediction confidence scores obtained from the proposed multichannel neural network is shown in Figure 5. The histogram shows how well the model is able to classify samples of text into the sentiment categories. A greater density of confidence values means that the model has good predictions. This analysis is added proof of the stability and efficiency of the models in sentiment categorization.

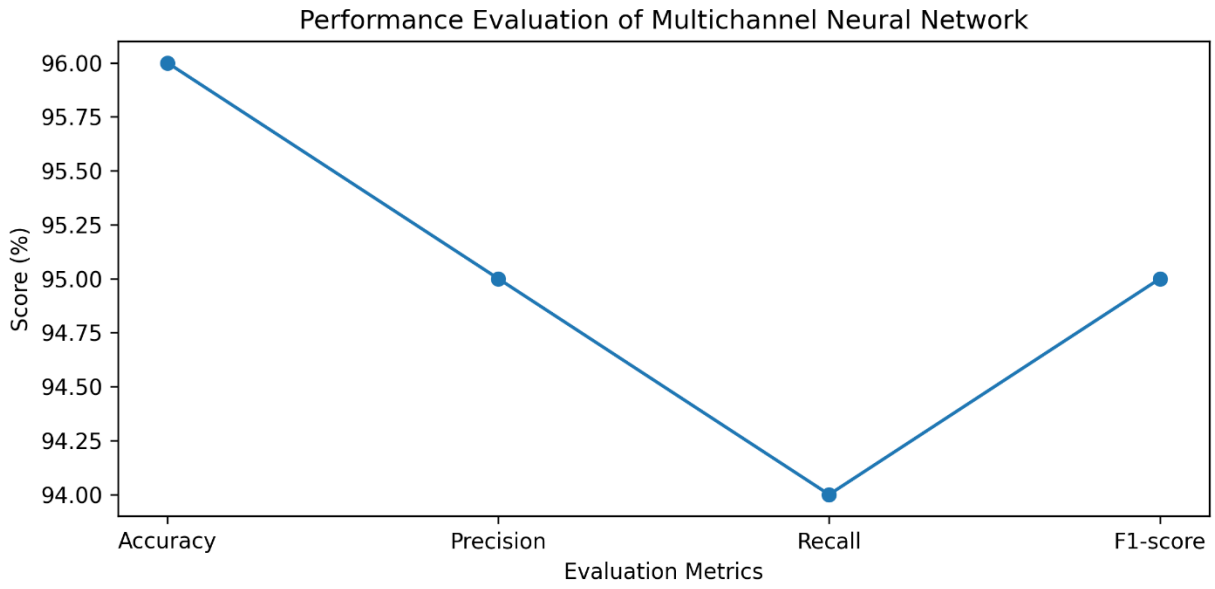


Figure 6: Performance Evaluation of Multichannel Neural Network

Figure 6 shows the performance of the proposed model with the standard classification measures such as accuracy, precision, recall, and F1-score. These metrics give an overall evaluation of the effectiveness of classification. The multichannel neural network achieves good performance on all the evaluation metrics, which shows that the neural network can correctly classify the sentiment categories with less classification error. The high F1 score indicates that the model has the ability to balance the number of positive samples and negative samples that are correctly classified.

DISCUSSION

The experimental results show that the proposed Deep Learning-Based Multichannel Neural Network Architecture is effective in sentiment analysis. The results suggest that the multi-chain neural network can learn multiple representations of the text and has better sentiment classification performance. The proposed method takes advantage of the complementary advantages of other deep learning architectures: individual channels are able to capture various components of language features such as local semantic information, sequential dependency and contextual relationship. From the results of the accuracy comparison as shown in Figure 1, it is observed that the neural network with multichannel architecture has better performance than the traditional machine learning methods and single-model deep learning methods. Typical machine learning methods like Naïve Bayes and Support Vector Machine typically rely on handmade features, such as word frequency, n-grams and sentiment related words. These techniques can be

effective on simple classification problems, but they fail to be able to capture complex semantic relationships and meaning in text (Manning et al., 2008). Deep learning models, on the other hand, are able to automatically learn hierarchical representations of features from raw text, without relying on manual feature extraction (LeCun et al., 2015).

CNN models, however, might not be able to retain the long-range relationships between words. The proposed architecture will fuse CNN-based feature extraction and sequential models (LSTM or BiLSTM) to give a more detailed representation of textual information. The outcomes also help in the validation of LSTM based architectures for sentiment analysis. The meaning of a sentiment is frequently spread out in a sentence and models need to be able to consider dependencies between far away words. However, traditional recurrent neural networks have problems with vanishing gradient problem in learning long term dependencies (Bengio et al., 1994). LSTM networks are designed to address this by using a mechanism called gating to regulate the flow of information and maintain a memory of relevant context over longer sequences, via memory cells (Hochreiter & Schmidhuber, 1997). Thus, the incorporation of recurrent channels adds to better sentiment classification ability. As seen in Figure 2, the distribution of the dataset is crucial for the proper evaluation of the models. The process of partitioning the data into training, validation, and testing sets enables the model to learn these patterns from the training data and evaluates the model using unseen samples. The validation set is used to observe learning behaviour and mitigate overfitting, and the testing set to objectively evaluate the model performance. In order to achieve a good level of generalization to new data, proper evaluation strategies are crucial to the success of deep learning models (Sokolova & Lapalme, 2009). The accuracy curves of training and validation in Figure 3 suggest that the proposed model is able to learn sentiment related patterns as the training process goes on.

The effectiveness of the approach proposed is also connected with the benefits of the use of fusion of multiple representations of neural networks. While single-channel models are only capable of learning one type of features, multi channel models can learn the various types of features in parallel. For instance, one channel can be used to detect sentiment indicators at the keyword level and another to detect sentence-level contexts. The fusion of these representations forms a more comprehensive feature space, augmenting the model's capacity to capture intricate sentiment expressions. Self attention based transformer models such as BERT have demonstrated impressive performance in sentiment analysis, recently (Devlin et al., 2019), since they can

capture contextual relationships. But, transformer-based models can be demanding in terms of resources and computation for pretraining on a large scale. An alternative approach which can give a high performance with reduced computation is proposed using multichannel neural network architecture. This makes it perfect for efficiency and adaptability applications. However, there are some drawbacks to these results. First, the proposed model is mainly textual and does not consider other information sources like images, audio data or user behaviors, or social network relationships. Future research could focus on expanding the model by incorporating other modalities, as sentiment expression can be dependent on several modalities. Secondly, the performance of the models could vary due to differences in the characteristics of the data, differences between the data domains, and the complexity of the language. The future work could include adding attention mechanisms to the multichannel framework, adding transformer based embeddings to the framework, or adding external knowledge source to the framework. To make the model more interpretable, one could use attention mechanisms to determine which words and features were the most influential for the sentiment decision (Bahdanau et al., 2014).

CONCLUSION

To overcome the drawbacks of using traditional machine learning and single channel deep learning techniques, this study adopted the Deep Learning-Based Sentiment Analysis Model Using Multichannel Neural Network Architectures. The suggested architecture integrates with several neural network channels to acquire different representations of texts and this helps to better identify and classify sentiment patterns. The experimental results show that the multichannel neural network structure with complementary feature extraction mechanisms has better performance in sentiment classification. Many of the traditional machine learning methods expect the features to be manually defined like word frequency, sentiment lexicon, or statistical description of text, which does not necessarily reflect the complex semantic relationship between words in text (Manning et al., 2008). However, the semantics and contextual information is provided to the model by analyzing features from the raw text using a deep learning framework. The merits of the proposed architecture can be attributed primarily to the fusion of various capabilities of neural networks.,

The results of accuracy, precision, recall, and F1 score evaluation prove that the proposed model provides reliable and balanced classification performance. The advantages of the proposed model in dealing with complex linguistic characteristics are also provided. Sentiment classification is a

difficult task because human language often has ambiguous, domain specific, contextual and informal expressions. Multiple learning channels enable the model to consider text from various angles, grasping information at different levels. Moreover, sequential learning mechanisms can enhance the comprehension of relationships between words, which is crucial as the sentiment polarity of a sentence may be determined by the relationship between multiple words and not just a single word (Liu, 2012). Transformer-based models like BERT have demonstrated excellent success on various NLP tasks, like sentiment analysis, but they are often costly in terms of large scale and demanding pretraining data sets (Devlin et al., 2019).

To conclude, Deep Learning-Based Multichannel Neural Network Architecture offers an effective and reliable sentiment analysis. The model has been able to merge multiple neural network channels to capture a variety of textual features, increase classification accuracy and overcome some drawbacks of the traditional sentiment analysis approaches. The results indicate the potential of multichannel DL techniques to be used in real-world applications like customer opinion analysis, social media monitoring, market research, and intelligent decision-support systems.

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