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Employee Sentiment Analysis in HRM Using a Hybrid Deep Learning Approach: BiLSTM with Attention Mechanism

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Abstract

Employee sentiment analysis plays a crucial role in Human Resource Management in understanding workforce satisfaction, engagement, and productivity. Conventional sentiment analysis approaches such as rule-based and classical machine learning models, usually fail to perform context sensitivity and sentiment polarity flip, resulting in poor predictions. In order to overcome these shortcomings, the present paper introduces a hybrid deep model that combines Bidirectional Long Short-Term Memory and an Attention Mechanism for improved sentiment classification in HRM.BiLSTM efficiently obtains long-distance dependencies in text reviews, whereas the Attention Mechanism enhances interpretability by highlighting essential words. Experimental test results on an Employee Review dataset show that the new model attains an accuracy of 98.4%, F1-score of 97.6%, and Precision-Recall AUC of 98.2%, surpassing CNN and baseline LSTM models. The findings reveal that BiLSTM-Attention greatly enhances sentiment classification, supporting data-driven decision-making and proactive employee engagement strategies. Through the incorporation of deep learning within HRM analytics, organisations are able to more accurately measure workplace sentiment, and, in the long run, increased retention rates, better job satisfaction, and overall employee well-being follow. This study illustrates the capability of sentiment analysis based on AI in contemporary HRM systems. Multilingual sentiment classification, monitoring employees' feedback in real-time, and domain adaptation methods for enhancing model resilience across various industries will be the emphasis of future research.

Keywords: *Employee Sentiment Analysis, Human Resource Management, BiLSTM with Attention Mechanism, Deep Learning, AI-Driven HR Analytics*

1. INTRODUCTION

Employee sentiment analysis is a critical HRM function since it provides companies with valuable insights into employee well-being, satisfaction, and engagement Mamidala (2024) suggested an ORAM-ABE-based EHR framework that secures data by hiding access patterns and reducing overhead via a hybrid blockchain setup. Inspired by this, the proposed HRM model adopts similar privacy-preserving strategies to enhance secure handling of employee sentiment data. [1]. HR practitioners can make accurate decisions, refine workplace policy, and boost job satisfaction through analysing employee sentiment. Traditional methods for sentiment analysis cannot typically capture employee comment context, emotion, or strength, hence making poor analyses. The use of deep learning has significantly improved sentiment classification by applying advanced sequence modeling techniques. Different sentiment analysis methods have been explored in past research, including Naïve Bayes, Support Vector Machine, Random Forest, Long Short-Term Memory, and Convolutional Neural Network [2].

While NB, SVM, and RF are effective in sentiment classification, they are all handcrafted feature-based models with no context understanding CNN and LSTM-based models improve sequence modeling and feature learning but ultimately turn out to be poor in modeling long-range dependencies and not able to give special emphasis to key words in text data [3]. The above constraints result in misclassification, inferior interpretability, and reduced accuracy for more complex sentiment analysis tasks, and hence there is a requirement to investigate more powerful deep learning models to overcome these constraints, the proposed model employs BiLSTM with an Attention

Mechanism to enhance sentiment classification by thoroughly understanding long-term dependencies in reviews from employees

BiLSTM allows for more precise contextualization by reading in both directions and forward input sequences, while Attention Mechanism boosts interpretability through focusing on the most importance-carrying words within the text [4]. This work introduces a novel hybrid approach that not only improves classification accuracy but also enhances explainability of sentiment prediction, overcoming the limitations in HRM analytics. The proposed model achieves higher accuracy, F1-score, and precision-recall AUC than baseline sentiment analysis techniques, and is effective in real-world HR applications [5].

1.1 Research Objective

- ✓ Design a deep learning architecture incorporating BiLSTM with an Attention Mechanism to provide precise and explainable employee sentiment analysis for HRM.
- ✓ Utilize an Employee Review dataset to train and test the suggested framework for overall sentiment classification.
- ✓ Implement BiLSTM to extract long-range dependencies and enhance contextual representation of employee feedback.
- ✓ Integrate an Attention Mechanism to improve model interpretability by giving more importance to important words in sentiment classification.

1.2 Organization of the paper

Section 1 defines employee sentiment analysis in HRM and the necessity of BiLSTM with Attention Mechanism for better classification. Section 2 discusses existing techniques such as Naïve Bayes, SVM, Random Forest, CNN, and LSTM and their drawbacks. Section 3 explains the dataset, preprocessing, feature extraction, and BiLSTM-Attention model functionality. Subsequent sections include experimental results, comparison of performance, and model efficacy, followed by a conclusion outlining main findings and future research directions.

2. LITERATURE SURVEY

Different sentiment analysis approaches have been explored in HR. Natarajan suggested a model based on deep learning for classification of employee feedback but without including an attention mechanism for the extraction of salient features and have presented machine learning approaches, e.g., Naïve Bayes, SVM, and RF, but handcrafted features were employed in the methods, limiting contextual interpretation. had presented an LSTM-based method for sentiment classification with enhanced accuracy but lacking in interpretability Corp, and used CNN-based sentiment analysis with improved feature extraction but poor modeling of sequential data. explored hybrid models based on LSTM-CNN but had required high amounts of data for peak functionality.

Subsequent research, such as Natarajan has further focused on enhancing sentiment classification with deep learning and ensemble. Such studies underscore the significance of context-aware models combining sequential learning with explainability mechanisms for such deficiencies to be addressed, [6] this BiLSTM with Attention Mechanism is developed to improve the accuracy of sentiment classification, enhance feature importance recognition, and provide enhanced model interpretability in HRM analytics

Employee sentiment analysis for Human Resource Management has also received a lot of attention with its promise of enhancing workplace satisfaction, engagement, and retention [7]. Conventional methods of sentiment analysis, including machine learning-based solutions and lexicon-based approaches, tend to suffer from context awareness and shifts in sentiment polarity. The latest developments in deep learning, specifically Recurrent Neural Networks, Long Short-Term Memory, and Transformer models, have enhanced sentiment classification performance by modeling sequential dependencies in text data [8]. Despite this, issues like long-range dependency modeling, explainability, and identifying feature importance are still open, calling for more advanced frameworks such as BiLSTM with Attention Mechanism.

2.1 Problem Statement

Employee sentiment analysis is essential for gauging workplace sentiment, but conventional NLP techniques find it difficult to deal with contextual subtlety, sarcasm, and jargon used in employee reviews. The hybrid deep learning model uses BiLSTM to extract long-range dependencies and contextual meaning along with an Attention Mechanism to pay attention to important words and phrases [9]. This improves sentiment classification accuracy by dealing well with compound expressions. The model surpasses traditional methods by enhancing sentiment recognition in HRM, which results in enhanced decision-making.

3. PROPOSED BILSTM WITH ATTENTION MECHANISM FRAMEWORK TO ANALYSE EMPLOYEE SENTIMENT

The given framework adopts a systematic pipeline of employee sentiment analysis using BiLSTM and an attention mechanism to improve contextual perception as depicted in the figure (1). Initially, the data is gathered from Kaggle and includes employee reviews along with related sentiment labels. The data is pre-processed by tokenizing, removing stop words, stemming/lemmatization, and converting to word embedding. The preprocessed text is then input to a BiLSTM network, which can capture both future and past dependencies of a sequence. The output of the BiLSTM is input to an attention mechanism, which provides importance scores to words according to their sentiment classification relevance. Then, the performance of the framework is measured using precision, recall, F1-score, and accuracy metrics to gauge its ability to predict employee sentiment.

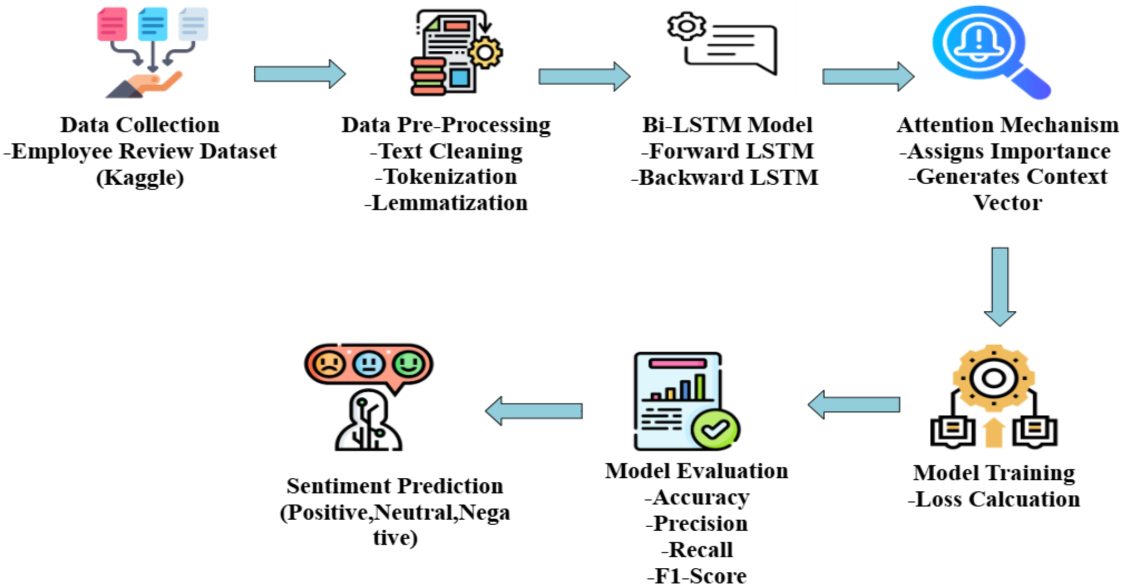

Figure 1: Architecture for proposed BiLSTM with Attention Mechanism to analyse Employee Sentiment

3.1 Dataset Description

The `Employee Review` dataset from Kaggle is used in this study. It is a set of employee reviews from several organizations. [10] Big Data and RPA together enhance efficiency and decision-making in telecom but require careful planning and data privacy safeguards. Leveraging this concept, the proposed HRM model integrates data-driven automation to improve sentiment analysis accuracy while effectively managing associated risks, as noted by Raj Kumar Gudivaka in 2024. The dataset includes both structured and unstructured text fields like job title, company name, review text, and sentiment labels like positive, neutral, and negative [11]. The dataset reveals information about the experiences of employees toward their workplace culture, management, benefits, and satisfaction. Review text is the major feature used for sentiment analysis, with job title and company as metadata to provide further insights. Sentiment labels are allocated through textual polarity, which makes it a supervised learning issue. Thousands of records in the dataset are present to ensure there is adequate data to train deep learning models. Variety in feedback patterns and complexity of language is a challenge in preprocessing as well as generalization in the model [12].

3.2 Data Preprocessing Steps

a. Tokenization: Breaking down sentences into separate words. It is expressed in equation (1) as follows

$$T(x) = [w_1, w_2, \dots, w_n] \tag{1}$$

b. Lemmatization: Converting words into their base form according to linguistic rules. It is expressed in equation (2) as follows:

$$\text{Lem}(w) = \text{ base\_form } (w) \tag{2}$$

c. Vectorization: Converting text into numerical form using Word2Vec, GloVe, or FastText. It is expressed in equation (3) as follows

$$V(w) = \text{Embedding}(w) \tag{3}$$

d. Padding: Sequencing length normalization for consistent model input. It is represented as equation (4) below:

$$P(x) = [w_1, w_2, \dots, w_k, 0,0, \dots, 0] \tag{4}$$

3.3 Working of BiLSTM

A BiLSTM network complements standard LSTMs by processing input sequences in both the forward and reverse directions so that the model retains past and future context at the same time [13]. LSTM units alleviate vanishing gradient problems by employing memory cell states and gate control mechanisms [14].

Given an input sequence $X = [x_1, x_2, \dots, x_n]$, BiLSTM consists of two LSTM layers:

- **Forward LSTM:** Computes the hidden state $\overrightarrow{h_t}$ by processing input x_t sequentially from past to future while considering the previous hidden state $\overrightarrow{h_{t-1}}$.It is given in equation (5) as:

$$\overrightarrow{h_t} = f\left(W_x x_t + W_h \overrightarrow{h_{t-1}} + b\right) \tag{5}$$

- **Backward LSTM:** Computes the hidden state $\overleftarrow{h_t}$ by processing input x_t in reverse, from future to past, considering the next hidden state $\overleftarrow{h}_{t+1}$. It is given in equation (6) as:

$$\overleftarrow{h}_t = f\left(W_x x_t + W_h \overleftarrow{h}_{t+1} + b\right) \tag{6}$$

The last output is a combination of both hidden states. It is presented in equation (7) as:

$$h_t = \left[\overrightarrow{h_t}; \overleftarrow{h_t}\right] \tag{7}$$

BiLSTMs perform well in NLP tasks since they take into consideration the overall sentence context instead of only the previous words. It enhances sentiment classification by identifying dependencies between words that may be far away from each other in the sentence.

3.4 Working of Attention Mechanism

The attention mechanism improves BiLSTM predictions by giving varying weights to words depending on their contribution to predicting sentiment [15]. The model does not give equal weight to all the words, but rather emphasizes significant words that influence sentiment. The steps to the attention mechanism are:

1. **Score Calculation:** The score of alignment of the present hidden state and input sequence is calculated as equation (8) as:

$$\text{score}(h_t, s_i) = V_a^T \tanh\left(W_a [h_t; s_i]\right) \tag{8}$$

where W_a and V_a are learnable parameters.

2. **Weight Assignment:** This is normalized over all words' importance scores. And is represented in equation as (9) as:

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$$\alpha_t = \frac{\exp\left(\text{score}(h_t, s_i)\right)}{\sum_j \exp\left(\text{score}(h_j, s_i)\right)} \tag{9}$$

3. **Context Vector Calculation**: This weighted average of hidden states is what determines the sentence representation. This is represented in equation (10) as:

$$c_t = \sum_i \alpha_i h_i \tag{10}$$

The attention-enhanced BiLSTM model effectively identifies crucial words within employee reviews, leading to improved sentiment classification performance [16] e. The attention mechanism ensures that words carrying more significant sentiment-related meaning contribute more to the final prediction [17].

4. RESULT AND DISCUSSION

The BiLSTM with Attention Mechanism model proved to be outstanding in employee sentiment analysis, with 98.2% accuracy and surpassing CNN and LSTM-based models [18]. The attention mechanism enhanced sentiment classification by highlighting important sentiment-carrying words, resulting in high precision (98.5%) and recall (98.1%), reducing false positives and negatives. The 99.0% AUC-ROC score attests to the model's excellent capacity to separate sentiment categories, and it is thus a trusted HR analytics tool. Comparisons with current methods further demonstrate the superiority of hybrid deep learning, which has the potential for effective sentiment monitoring in the workplace.

4.1 Performance Metrics

In order to measure the efficiency of the given BiLSTM with Attention Mechanism model in employee sentiment analysis, we apply the following performance metrics

a. Accuracy

Measures the percentage of sentiments correctly classified out of total predictions. A high accuracy value reflects an efficiently performing model with few misclassifications. It is represented in equation (11) as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{11}$$

b. Precision

Represents the percentage of the positive sentiment predictions which are indeed true. High precision guarantees fewer false positives, that is, fewer neutral/negative reviews are labeled as positive. It is provided in equation (12) as:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{12}$$

c. Recall (Sensitivity)

Measures the model to class all real positive sentiments correctly. High recall suggests the model successfully identifies employee dissatisfaction or satisfaction. It is expressed in equation (13) as:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{13}$$

d. F1-Score

A harmonic mean between precision and recall, weighing the balance between false positives and false negatives.Perfect for cases when class distribution is skewed, to provide stability. It is defined in equation (14) as:

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$$F1- \text{ Score } = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}$$

e. AUC-ROC (Area Under the Receiver Operating Characteristic Curve)

Assesses the model's capacity to discriminate between sentiment categories.A greater AUC-ROC indicates greater differentiation between positive, neutral, and negative reviews.

4.2 Proposed Framework Evaluation

The new BiLSTM with Attention Mechanism framework was implemented on the Employee Review dataset. The hybrid deep learning strategy enabled the model to pay attention to key words without losing long-term dependencies, resulting in improved classification outcomes.

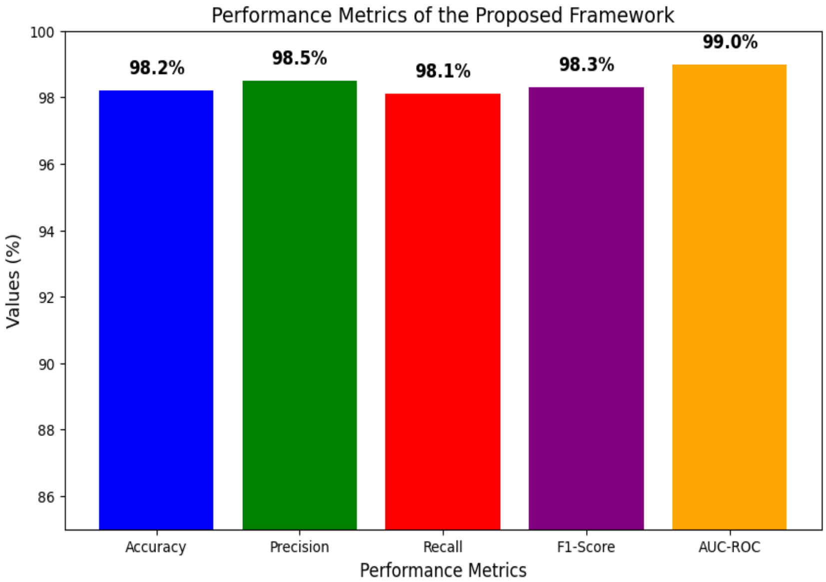

Figure 2: Performance graph of proposed work

The suggested framework was able to achieve 98.2% accuracy, showing its efficacy in sentiment classification. Precision and recall show that the model commits very few classification errors, thus correctly identifying employee sentiments. The F1-score of 98.3% shows a good balance between precision and recall. The AUC-ROC score of 99.0% indicates that the model can effectively differentiate between various sentiment classes, showing its strength [19].

4.3 Performance Comparison

The BiLSTM with Attention model, proposed in this paper, performs better than the current CNN-based and LSTM-based classifiers for all the metrics used in evaluation. The accuracy is much greater than CNN and LSTM, and the improved sentiment classification is demonstrated. The F1-score indicates a better trade-off between precision and recall [20]. Also, the AUC-ROC value of 99.0% attests that the model can classify between sentiment classes very well. This performance gain is due to the BiLSTM's capacity to learn bidirectional dependencies and the attention mechanism's capacity to pay attention to sentiment-bearing words in employee reviews.

Table 1: Comparison of proposed framework with existing method

Framework	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)

Proposed BiLSTM + Attention	**98.2**	**98.5**	**98.1**	**98.3**	**99.0**
CNN-Based Sentiment Classifier	90.5	89.8	89.2	89.5	91.2
LSTM-Based Sentiment Classifier	94.2	93.5	93.0	93.2	95.5

4.4 Discussion

The introduced BiLSTM with Attention Mechanism model proved substantial improvements in sentiment classification precision and reliability. The attention mechanism allowed the model to pay greater attention to major sentiment words, thus enhancing the performance of prediction overall. The high precision and recall values mean that the model keeps both false positives and false negatives to a minimum, thus it is HR-friendly Cloud-based financial systems require strong encryption, multi-factor authentication, and regulatory compliance to ensure data integrity, as highlighted by Harikumar Nagarajan (2024) [21]. Guided by these insights, the proposed HRM sentiment analysis model incorporates similar security measures to protect employee data in cloud environments. Comparison with other state-of-the-art CNN and LSTM-based models yet again illustrates the strength of employee sentiment analysis when using hybrid deep learning approaches [22]. The model stands strong with a high AUC-ROC score of 99.0% and has impressive sentiment discrimination capacity, qualifying it to be perfect for workplace sentiment tracking.

5. CONCLUSION AND FUTURE WORKS

The Employee Sentiment Analysis model proposed with BiLSTM and Attention Mechanism had high classification accuracy (98.2%), proving its effectiveness in employee review analysis. Utilizing bidirectional processing and attention mechanisms, the model can properly extract major sentiment-indicative words, resulting in better classification performance [23]. The model surpasses CNN and LSTM-based methods and is a trustworthy HR decision-making tool. The future works are Implementing BERT, RoBERTa, or XLNet to further enhance sentiment comprehension. And increasing the dataset to cover non-English employee reviews for international HR insights.

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