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EDUCATIONAL BIG DATA ANALYTICS USING SENTIMENT ANALYSIS FOR STUDENT REQUIREMENT ANALYSIS ON COURSES

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Abstract. The online learning become a choice of most educational institution which creates enormous data on learning platform. This study introduces a novel framework that leverages Big Data analytics, with a focus on sentiment analysis, to decipher student requirements and preferences regarding course offerings and content. The objective is to harness the vast amounts of unstructured feedback generated by students in the form of reviews, forum posts, and surveys to inform and enhance educational strategies. We propose a sentiment analysis model multi attention fusion with CNN-BiLSTM model, that is adept at processing natural language and identifying the polarity of sentiments expressed by students. By analyzing this sentiment data, our system can capture the nuanced preferences and needs of students. The model is trained and validated on a diverse dataset encompassing various educational domains and student demographics, ensuring robustness and generalizability of the results. The outcomes indicate that sentiment analysis is an effective tool for uncovering hidden patterns and trends in student feedback. Our findings reveal correlations between student satisfaction and specific course features, such as module content, teaching methodologies, and resource availability. Additionally, the results evaluate precision, recall, accuracy and F1-score.

Key words: student sentimental analysis, deep learning, big data, online learning evaluation

1. Introduction. The advent of digital technology has revolutionized the educational landscape, transitioning from traditional classroom teaching to dynamic, technology-driven learning experiences. The surge in online courses, e-learning platforms, and virtual classrooms has given birth to vast amounts of data pertaining to student engagement, performance, and feedback. Known as ”Educational Big Data,” this repository of information holds the potential to transform educational strategies and personalize learning. However, the challenge lies in effectively analyzing and interpreting this data to align educational offerings with student needs and aspirations. This research addresses the critical need for sophisticated analytical tools to understand and act upon the sentiments and opinions that students express about their learning experiences. Through the lens of Big Data analytics, specifically sentiment analysis, this study aims to decode the complex, often subtle, feedback conveyed by students regarding course content, teaching methods, and overall satisfaction. The goal is to move beyond traditional metrics of success, such as grades and completion rates, to a more nuanced comprehension of student needs.

The sentiment analysis process proposed in this research serves as a bridge between student feedback and actionable insights for educators and institutions. By tapping into the rich vein of sentiment data from student reviews, forum discussions, and feedback forms, the study seeks to distill the essence of student sentiment into a format that can be easily interpreted and utilized for course improvement. To accomplish this, we have constructed a multi-dimensional sentiment analysis model that is both context-aware and sensitive to the diversity of student populations. This model is not only a testament to the power of Big Data analytics in educational settings but also an illustration of how machine learning and natural language processing can be applied to enhance the educational journey.

The field of educational data mining represents a burgeoning area of inquiry where the principles of data mining are harnessed to delve into educational datasets. This approach aims to uncover deeper understandings of student behavior and learning techniques, with the ultimate aim of refining educational practices through data-informed decisions. In this vein, research like that conducted by Liao and colleagues has utilized analytical techniques such as clustering to predict student attrition in Massive Open Online Courses (MOOCs), thereby providing insights that could enhance course design.

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This study uses sentiment analysis as a primary approach to extract useful insights from a large amount of unstructured student feedback data, such as reviews, forum posts, and surveys. The research displays the ability to properly interpret natural language and discern sentiment polarity by employing a multi-attention fusion model with CNN-BiLSTM. Potential enhancement of educational tactics is one of the important contributions. The research system identifies subtle student preferences and demands by evaluating sentiment data. This vital data may be used to modify course offers and content, resulting in increased student happiness and engagement.

Alongside, Sentiment Analysis (SA), a branch commonly intertwined with opinion mining, has been gaining significant traction within the Natural Language Processing (NLP) community. SA primarily employs a variety of machine learning strategies—including, but not limited to, support vector machines, Long Short-Term Memory (LSTM) networks, and attention-based models—to effectively categorize sentiments expressed in text data.

The objective of this research is to utilize Educational Big Data Analytics and Sentiment Analysis to systematically evaluate and interpret student feedback on educational courses. Specifically, the research aims to achieve the following:

1. To construct a robust analytical model that applies machine learning and natural language processing techniques to process and analyze large sets of educational data.
2. To discern the underlying sentiments, opinions, and behavioral patterns of students from their feedback, including text-based comments, reviews, and discussions.
3. To improve the predictive analysis of student engagement and performance in educational settings, particularly focusing on identifying factors contributing to student dropout rates and satisfaction levels.

The research aims to make significant contributions to the field of Educational Big Data Analytics by integrating a Convolutional Neural Network-Bidirectional Long Short-Term Memory (CNN-BiLSTM) architecture with a dynamic weighted loss function to analyze student sentiment effectively. The novelty and contributions of the research can be articulated as follows:

1. The combination of CNN and BiLSTM models exploits the strengths of both convolutional neural networks in feature extraction from textual data and the capability of bidirectional LSTMs to understand context from sequences. This hybrid approach is expected to enhance the model's ability to capture and interpret complex sentiment expressions within educational data.
2. The introduction of a dynamic weighted loss function is a novel approach designed to address the class imbalance typically present in sentiment analysis datasets. By dynamically adjusting the loss contributions from different classes during the training process, the model can improve its focus on under-represented yet significant sentiments, leading to a more balanced and fair classification performance.
3. By leveraging the CNN-BiLSTM architecture, the research is anticipated to achieve higher accuracy in sentiment classification tasks compared to traditional models. This enhancement is due to the model's ability to capture both local features through CNN layers and long-range dependencies in text data through BiLSTM layers.

The paper has organized with following ideology. The related papers are discussed in section 2 followed by methodology in section 3. Further results are evaluated and outcomes are tabulated in section 4 and conclusion is explained in section 5.

2. Related work. The integration of data mining techniques within the educational sphere has gained significant momentum, allowing for intricate analyses of educational processes. Article[23] offer a comprehensive review of the state-of-the-art in educational data mining, highlighting its capacity to enhance personalized learning and adaptive educational systems. Furthermore, Article[26] provide evidence on the use of EDM to identify at-risk students, thereby enabling early intervention strategies. Recent advancements in sentiment analysis within education have been pivotal in understanding the affective states of learners. Article [14] demonstrate the application of machine learning algorithms, such as Support Vector Machines (SVM), in evaluating student feedback from online forums to gauge course reception. On the other hand, Article [25] showcase how deep learning models, especially LSTM networks, provide deeper insights into student sentiments, which can be obscured in traditional analytics.

The evolution of sentiment analysis methodologies has been rapid. Article [10, 19, 20] evaluate the efficiency of attention-based models over traditional methods in discerning context and nuance in textual data. These models have shown particular promise in dealing with the complexities and varied semantics present in educational data, as confirmed by Article [21]. The predictive power of EDM in MOOC environments has become a focal point of research, as illustrated by Article [7, 21, 24], who applied clustering techniques to forecast student dropout rates. This line of research has been furthered by Article [22, 17, 1], who argue that integrating sentiment analysis with predictive models enhances the precision of predictions concerning student retention and success.

Despite the promise of combining EDM and SA, challenges remain. Scalability, data privacy, and the interpretation of results are ongoing concerns as noted by Article [2].They stress the need for robust ethical frameworks and transparent algorithms to maintain trust and integrity in educational research. Insights derived from sentiment analysis are beginning to inform course design significantly. Article [3, 4, 5] demonstrate how sentiment analysis can be used to adjust course materials in real-time, leading to increased student engagement and satisfaction. Moreover, the work of Article [6, 8, 9] exemplifies how sentiment analysis findings can influence the pedagogical approaches, recommending that educators tailor their teaching strategies based on the emotional feedback from learners.

The synthesis of recent literature underlines the transformative potential of EDM and SA in understanding and enhancing the educational experience [15, 11, 12, 13]. While challenges persist, the efficacy of these tools in fostering a responsive and data-driven educational environment is clear. Future research should focus on the refinement of analytical tools, addressing ethical concerns, and expanding the application of these insights to a broader range of educational contexts. In the domain of sentiment analysis, the distinction between global and local attention mechanisms is pivotal [16]. Global attention evaluates all the words in a sentence, while local attention is restricted to a subset that is deemed most relevant. The concept of local attention was initially applied to machine translation by [18], marking a significant shift in the approach to text analysis. Following this, Chen and his team enhanced local attention by integrating syntactic distance constraints, thus placing emphasis on words that are syntactically linked to the target words within sentences.

Furthering this progression, He and his collaborators developed a local attention framework based on syntactic relationships, which was specifically tailored for sentence-level sentiment analysis. Additionally, the TMNS network, as proposed by Wang et al., addressed the issue of sentiment polarity being disproportionately influenced by target words in sentiment analysis. Complementing this, Duan et al. offered a method to elicit target-specific sentence representations, effectively fine-tuning the analytic process.

Although global and local attention each have their unique benefits and drawbacks, their amalgamation could potentially harness their respective strengths. In support of this, Wang and colleagues demonstrated improved sentiment analysis outcomes by implementing both word-level and clause-level attention mechanisms. Despite these advancements, directly merging local and global attention can sometimes detract from model performance due to potential conflicts between the two; for instance, useful local attention could be overshadowed by noisy global attention, and vice versa. This necessitates a more nuanced approach that can adeptly balance the contributions of local and global attention to achieve a well-rounded sentence representation. Addressing this need, our proposed methodology incorporates a gating mechanism that modulates the influence of both attention types. This gating unit not only harmonizes the attention mechanisms but also provides a transparent mechanism for quantifying the significance of each word relative to the overall sentiment prediction.

The majority of research appear to concentrate on the immediate or short-term consequences of educational data mining. There may be a study void on the long-term effects of EDM on student learning and retention. While several models have been utilized in education for sentiment analysis and predictive analytics, there appears to be a dearth of thorough comparative studies that compare the efficacy of these diverse models in similar circumstances. Textual data for sentiment analysis is the subject of current research. Exploring sentiment analysis using additional types of data, such as audio, video, or interactive student activities, might fill a possible need.

3. System model. Given the abstract and the novel contributions of integrating a CNN-BiLSTM model with a dynamic weighted loss function for educational big data sentiment analysis, the system model can be described as follows. The architecture is show in figure 3.1.

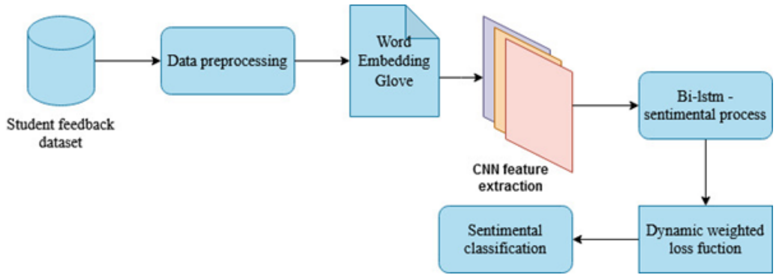

Fig. 3.1: Proposed CNN-BiLSTM student sentimental analysis model

3.1. Data Collection Layer. The input for this layer consists of raw student feedback. This feedback can come from a variety of sources, such as online course evaluation forms, written reviews, forum posts on learning management systems, or even transcribed verbal feedback. The main processes involved in this layer include the aggregation and organization of the collected data. Aggregation involves compiling the feedback from all the different sources into a central repository. Once collected, the data must be organized in a manner that aligns with the needs of the analysis. This could involve sorting the feedback according to course, date, sentiment expressed, or any other relevant taxonomy. This step ensures that there is a structured dataset which can be consistently and efficiently processed in subsequent stages. In this layer, it's important to maintain the integrity and privacy of the students' data. Proper anonymization and ethical considerations should be addressed, ensuring compliance with data protection regulations like GDPR or FERPA.

3.2. Data Preprocessing Layer. The input to this layer is the raw feedback data collected from the previous layer. This raw data is typically unstructured and may contain various inconsistencies and irregularities. Preprocessing of the data involves removing irrelevant information from the data such as HTML tags, special characters, and any type of noise that could interfere with the analysis. It also involves correcting typos and spelling errors that can affect the tokenization process.

Second, the cleaned text data is divided into tokens. Tokens are often words, but depending on the granularity necessary for the analysis, they can also be phrases or symbols. Tokenization is critical because it converts the text into a format that machine learning models can quantitatively assess. Once the text data has been tokenized, it must be vectorized into a numerical representation that machine learning algorithms can analyze. Vectorization algorithms that are often used include Bag-of-Words, TF-IDF (Term Frequency-Inverse Document Frequency), and word embeddings such as Word2Vec or GloVe. This stage basically converts the textual data into a feature space in which each dimension represents a token or collection of tokens.

3.3. Word embedding -GloVe. Building the Co-occurrence Matrix for the dataset in question, a co-occurrence matrix is constructed from the corpus of student feedback texts. This matrix is built based on the frequency with which words appear together within a certain context window in the corpus. Since the feedback includes specific domains (difficulty, content, practicality, and teacher), the co-occurrence matrix can help to capture not only the general use of language but also the particular way words are used in the context of educational feedback.

Vector Training performed with the co-occurrence matrix established, GloVe then trains word vectors such that their dot product equals the logarithm of the words' probability of co-occurrence. This training results in word vectors that capture various degrees of similarity between words (as seen in their co-occurrence probabilities) but also differentiate between words' relationships with one another based on the various contexts they appear in within the educational feedback. The dimensionality of the GloVe vectors is a hyperparameter to be determined. Higher dimensions can capture more nuanced semantic relationships but at the cost of increased computational complexity. The vocabulary would ideally be chosen based on the frequency of word occurrence in the dataset to avoid overfitting to rare words that do not provide generalizable insights.

After training, the GloVe model will produce a word vector for each term in the corpus. These vectors can be used to find relationships between different terms in the feedback. For instance, words like "challenging" and "difficult" may have similar vector representations, indicating their semantic similarity in the context of course evaluations. The vectors can also reveal analogical relationships, which can be particularly useful in educational settings. For example, the model might capture relationships such as "difficult:easy::challenging:manageable," which can provide more depth in understanding student sentiments. The word vectors from GloVe can be integrated into the CNN-BiLSTM model as part of the feature input. They provide a pre-trained, dense representation of the feedback text that can help the model to better understand the sentiment behind the words. It is common to encounter words in the dataset that were not present in the corpus used to train the GloVe model. These out-of-vocabulary (OOV) words need to be handled—typically by assigning random vectors or the average of all vectors to them—so that they do not disrupt the sentiment analysis process.

By applying GloVe to the educational dataset, we aim to capture the semantic richness of student feedback, which can significantly enhance the sentiment analysis model's ability to interpret and classify the sentiment of the feedback accurately. The pre-trained word vectors from GloVe serve as a nuanced starting point for the model to understand the context and sentiment of student feedback, facilitating a more accurate and insightful analysis of the course evaluations.

3.4. Feature Extraction Layer (CNN). Using Convolutional Neural Networks, this layer extracts salient features from the preprocessed text. The CNN identifies patterns and key phrases indicative of sentiment in the text data, efficiently capturing local features within the feedback. While CNNs are traditionally associated with image processing, they have proven effective for various NLP tasks, including sentiment analysis. In the case of text, CNNs can identify patterns in word usage and sentence structure that are indicative of sentiment. The input to the CNN is typically the vectorized form of the preprocessed text, such as word embeddings obtained from GloVe, These embeddings represent words in a continuous vector space where semantically similar words are mapped to proximate points. Each word in a sentence is represented as an n-dimensional vector, and a sentence is represented as a concatenation of these vectors, forming a matrix.

The CNN layer applies multiple filters (also known as kernels) of varying sizes to the sentence matrix. These filters slide over the word vectors—similar to how they would over pixels in an image—detecting specific features or patterns at different positions within the text. Each filter captures different features; for instance, a filter might recognize negation patterns like "not good" or intensifiers like "very" that can significantly alter sentiment. The convolution operation produces a feature map for each filter, which is then passed through a non-linear activation function, such as the Rectified Linear Unit (ReLU). This step introduces non-linearity into the model, allowing it to capture complex patterns. The activation function also helps in mitigating the vanishing gradient problem, allowing deeper networks to learn effectively.

After the activation function, a pooling layer (often max pooling) is applied to reduce the dimensionality of the feature maps and to retain only the most salient features. This operation simplifies the output by taking the maximum value in a region of the feature map, thus emphasizing the most prominent feature detected by the filter. Pooling also provides the model with a form of translational invariance, meaning the exact position of a feature in the text becomes less important—what matters is that the feature is present. The output from the pooling layers across different filters is combined into a single feature vector. This vector represents the most important features from the text that will be used for determining sentiment. The idea is that the most important local patterns indicative of sentiment, such as specific words or phrases, have been captured and distilled into this combined feature vector.

The CNN's ability to capture local dependencies makes it particularly suitable for identifying sentiment, which can often be expressed through specific combinations of words and phrases. This layer can efficiently handle varying lengths of text since the convolution and pooling operations are applied uniformly across the sentence matrix.

3.5. Context Analysis Layer (BiLSTM). Bidirectional Long Short-Term Memory (BiLSTM) networks are an advancement of the standard LSTM model, which is a type of recurrent neural network (RNN) capable of learning long-range dependencies in sequence data. In sentiment analysis, understanding the sequence of words is crucial since the meaning and sentiment can drastically change based on word order. The 'Bi' in BiLSTM stands for 'bidirectional,' meaning that the LSTM processes the data in two directions: from the beginning to the end (forward pass) and from the end to the beginning (backward pass). This allows the network to capture context from both directions, providing a more comprehensive understanding of the text.

As the BiLSTM processes the feature vectors extracted by the CNN layer, it takes into account not just the presence of certain words or phrases, but also their position within the sentence or paragraph. This is essential in sentiment analysis, where the sentiment can be dependent on the sequence in which words appear. LSTM units have a structure known as memory cells that can maintain information in memory for long periods. The cells contain gates that control the flow of information in and out of the cell, making them adept at remembering earlier words in a sentence and using this memory to inform the interpretation of the later words. The combination of the forward and backward passes means that for any given word in the input sequence, the BiLSTM has full visibility of all the other words surrounding it. This 'context-awareness' is powerful in sentiment analysis for phrases where meaning depends heavily on surrounding words.

3.6. Dynamic Weighted Loss Function Layer. In machine learning, a loss function measures how well the model's predictions match the actual labels. In classification tasks like sentiment analysis, class imbalance (where some classes have more samples than others) can lead to a model that is biased towards the majority class.

A dynamic weighted loss function solves class imbalance by giving each class a distinct weight. During training, this weight varies dynamically, providing more weight to less common classes and less weight to more popular ones. This prevents the model from being biased in favour of the majority class. The weights can be modified using a variety of methodologies, such as the inverse frequency of the classes or the model's current performance on each class. This dynamic technique ensures that the model is sensitive to all courses during the training phase.

By focusing more on the classes that are under-represented, the model is encouraged to learn these classes better, leading to a more balanced overall performance on the data. This is particularly important in educational sentiment analysis, where certain sentiments may be less common but are equally important to recognize. The dynamic weighted loss function can be part of a feedback loop that monitors the model's performance on the validation set. Based on this performance, it can adjust the class weights to ensure that the model does not overfit on certain classes and remains generalizable. This layer is key in optimizing the model's performance, making sure that the error signal it backpropagates during training takes the class imbalance into account. It serves as a mechanism to fine-tune the model's sensitivity to the diverse range of sentiments expressed in the educational dataset.

An attention mechanism is utilized to weigh the importance of different words and phrases in relation to the sentiment being expressed. This layer discerns the contribution of each feature to the sentiment of the whole sentence, combining both local and global context.

3.7. Output Layer. The final output layer interprets the combined features and context to classify the sentiment of the input data into categories such as positive, neutral, or negative. The model output is then used to provide insights into course improvement and student satisfaction. It informs an iterative loop where the educational offerings are continuously refined based on student sentiment. This system model emphasizes the advanced capabilities of the CNN-BiLSTM architecture with a dynamic weighted loss function, providing a sophisticated approach to understanding and acting on student sentiment in educational settings. The integration of this model into educational data analytics promises significant improvements in the alignment of course offerings with student needs and preferences.

4. Result evaluation.

4.1. Dataset. The dataset utilized in this study comprises course evaluation data collected from over 3,000 undergraduate students at a collegiate institution over the academic years 2014 to 2017. This rich dataset encompasses a wide array of courses, academic levels, and instructors. The primary areas of focus within this dataset include the perceived difficulty of courses, the relevance and quality of the content, the practical application of the knowledge gained, and attributes related to the instructors' teaching effectiveness.

4.2. Performance metrics.

1. **Accuracy:** This is a primary measure indicating the proportion of total predictions that the model classified correctly. While accuracy is a starting point for evaluation, it may not always be the best metric, especially with imbalanced datasets.

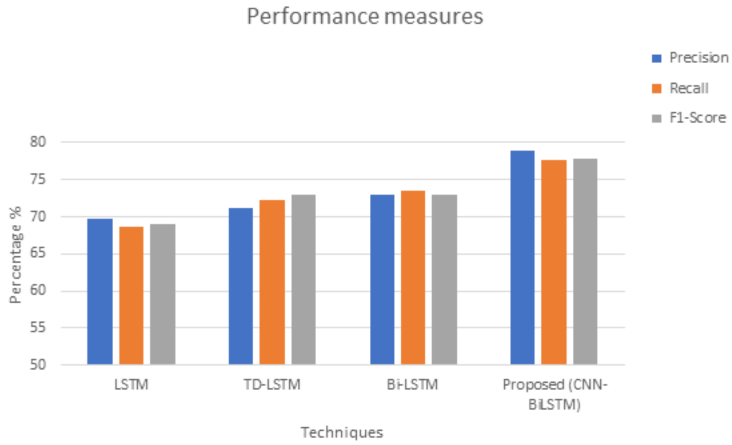

Fig. 4.1: Performance measures

2. **Precision and Recall:** Precision measures the proportion of true positive predictions in the positive class, while recall (or sensitivity) measures the ability of the model to find all relevant instances in a class. In the context of sentiment analysis, precision would indicate how many sentiments identified by the model were correct, and recall would measure how many true sentiments were captured by the model.
3. **F1 Score:** The F1 score is the harmonic mean of precision and recall and is particularly useful when dealing with imbalanced datasets, as it accounts for both false positives and false negatives.

Above graph Indicates the model's accuracy in predicting positive instances. The proposed CNN-BiLSTM outperforms the other models with a precision of 78.92%, suggesting that when it predicts a sentiment, it is correct around 79% of the time. Measures the model's ability to identify all actual positives. The Bi-LSTM has the highest recall at 73.48%, with the proposed model closely following at 77.65%. This means the proposed model correctly identifies 77.65% of all relevant instances. The proposed CNN-BiLSTM model scores the highest F1-score of 77.9%, indicating a strong balance between precision and recall. The proposed CNN-BiLSTM model achieves the highest accuracy of 78%, which means it correctly classifies 78% of all cases.

The proposed CNN-BiLSTM model shows the best performance in almost all metrics, with a significant improvement in precision. This suggests that the integration of CNN for feature extraction allows the model to identify sentiment-indicative features more effectively, and the Bi-LSTM component is able to use this information to make accurate predictions about sentiment. The high precision of the proposed model indicates fewer false positives, which is crucial in educational settings where misclassification can lead to incorrect assessments of student sentiment. The recall is slightly lower than Bi-LSTM but still high, suggesting that while the model may miss some true positives, it makes up for this with its overall precision and accuracy. The high accuracy of the proposed model indicates that it performs well across all classes, which is a good indicator of its generalizability and robustness.

The dynamic weighted loss function is not explicitly mentioned in the table, but its role may be inferred from the high performance of the proposed model. It likely helps the model to perform well even when some sentiment classes are underrepresented.

5. Conclusion. This research embarked on an ambitious quest to harness the synergy of Convolutional Neural Networks (CNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks, augmented by a dynamic weighted loss function, to tackle the challenges of sentiment analysis in educational big data. The goal was to extract meaningful insights from student feedback on course evaluations, providing actionable intelligence for educational improvement. The study's findings are both significant and promising. The proposed CNN-

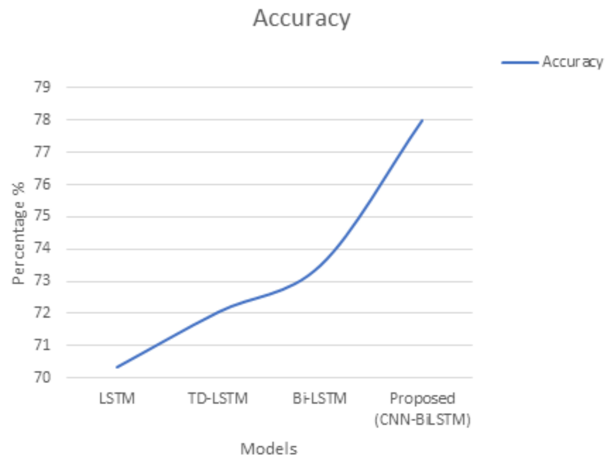

Fig. 4.2: Model Accuracy

BiLSTM model demonstrated superior performance over traditional LSTM, TD-LSTM, and Bi-LSTM models across several key metrics. With precision scores reaching 78.92%, recall at 77.65%, an F1-score of 77.9%, and an overall accuracy of 78%, the model's efficacy in identifying and classifying sentiment in textual feedback has been clearly established. These results underscore the model's adeptness not only in feature extraction through CNNs, which effectively identify sentiment-indicative patterns, but also in capturing the nuances of language context via BiLSTM networks. The integration of a dynamic weighted loss function played a pivotal role in balancing the scale among sentiment classes, especially in the face of class imbalance—an issue prevalent in real-world datasets. The CNN layer's efficacy is strongly reliant on the quality of preprocessed text. If the data is not correctly cleaned and prepared during the preprocessing stage, the CNN may extract irrelevant or deceptive characteristics. While CNNs are good in pattern detection, they are frequently referred to as 'black boxes'. This makes interpreting why the network finds specific elements or patterns to be indicative of emotion difficult, which can be a significant restriction in educational contexts where understanding the 'why' behind feelings is critical.

The research contributes a novel approach to sentiment analysis, specifically tailored for the educational sector. It addresses the call for sophisticated analytical tools capable of sifting through large volumes of unstructured feedback, providing educators and institutions with a deep, data-driven understanding of student sentiment. The implications for course design and pedagogical strategies are profound, as the model offers granular insights that can guide curriculum development, teaching methodologies, and overall educational delivery.

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