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The superior performance of the 64-unit model is particularly notable when compared to the other two configurations. The 32-unit configuration, though computationally efficient, frequently underperformed in negative sentiment detection—likely due to underfitting. Its limited capacity was insufficient to model the diversity and subtlety of user complaints, especially in aspects like Comfort and Safety, which often involved less explicit or emotionally complex language.

In contrast, the 128-unit setup, while sometimes equaling or surpassing the 64-unit performance on some negative sentiment tasks (e.g., Information, Comfort), showed signs of overfitting. This configuration likely picked up too much noise in the training data, which hurt its generalization to new examples. In particular, it suffered from a drop in positive sentiment classification in some categories (e.g., Information, which dropped to 90.39%) with increased model capacity, which is evidence of the risk of diminishing returns with larger architectures.

Further, the model's consistently higher accuracy in positive sentiment classification across all categories and configurations captures the simpler, more regular language generally used to convey satisfaction. Positive sentiment will tend to feature standard patterns and stronger sentiment cues, which are more easily detected by both CNN filters and LSTM memory cells. Negative sentiment is more linguistically diverse, being more likely to contain sarcasm, indirect insults, or contextual references that expend effort on both lexical and sequential models.

These results validate the necessity of quality embedding and model tuning. The use of 300-dimensional FastText embeddings, which were trained on massive corpora and could learn subword-level meaning, provided rich input representation that allowed the CNN-LSTM architecture to perform well even with moderate model complexity. The 64-unit model exploited the rich input without overfitting, thereby being the best configuration for this classification task.

In summary, the integration of text-to-sequence encoding and 300-dimensional FastText embeddings with a 64-unit CNN-LSTM architecture permitted accurate classification of sentiment and service dimensions in noisy and unstructured user review data. The study underlines the necessity for balancing model complexity with the richness of input representation and with the inherent variability of the classification problems. The findings also suggest that further gains can be achieved through the application of more advanced contextual embedding techniques, e.g., transformer-based models, or with the addition of attention mechanisms, which potentially capture the finer and contextually sensitive nature of sentiment—particularly in such subtle domains as safety. Such gains could lead to greater model robustness and transparency when deployed in real-world sentiment analysis applications.

4. CONCLUSION

This study developed and validated a CNN-LSTM model that aims to classify sentiment and extract aspects at the same time from Gojek user feedback. Based on a text-to-sequence input and 300-dimensional FastText embeddings, the said model was capable of deriving semantic relationships and context dependencies from noisy user-written text data. Experimental results indicated that the 64-unit configuration of the CNN-LSTM model provided the best trade-off between model complexity and generalizability, with the best accuracy across most sentiment and aspect classes. The improved performance of the model in positive sentiment classification and its ability to handle complicated and diverse negative feedback confirm the strength of combining pretrained embeddings with a hybrid CNN-LSTM structure. The results suggest that precise adjustment of model capacity is required to avoid underfitting or overfitting when faced with complex natural language tasks. In short, the proposed CNN-LSTM model is a robust approach to summarizing useful insights from large volumes of customer opinions to provide useful information that can be used to improve service quality and user satisfaction in online platforms like Gojek. Future work can explore the addition of more advanced embedding techniques, i.e., transformer models or attention mechanisms, to better learn nuanced and context-dependent sentiment nuances via features such as safety. These additions can possibly improve the accuracy and interpretability of sentiment systems in real-world applications.

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