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Transfer Learning Approach for Sentiment Analysis in Low-Resource Austronesian Languages Using Multilingual BERT

Li Wen Hao*[1], Robert Kuan Liu[1]
Email: wen.hao@monash.edu; kuan.liu@monash.edu
[1]*Monash University, Malaysia campus, Jalan Lagoon Selatan, 47500 Subang Jaya, Malaysia*
*Corresponding Author

Abstract
Sentiment analysis for low-resource languages, particularly Austronesian languages, remains challenging due to the limited availability of annotated datasets. Traditional approaches often struggle to achieve high accuracy, necessitating strategies like cross-lingual transfer and data augmentation. While multilingual models such as mBERT offer promising results, their performance heavily depends on fine-tuning techniques. This study aims to improve sentiment analysis for Austronesian languages by fine-tuning mBERT with augmented training data. The proposed method leverages cross-lingual transfer learning to enhance model robustness, addressing the scarcity of labeled data. Experiments were conducted using a dataset enriched with augmentation techniques such as back-translation and synonym replacement. The fine-tuned mBERT model achieved an accuracy of 92%, outperforming XLM-RoBERTa at 91.41%, while mT5 obtained the highest accuracy at 99.61%. Improvements in precision, recall, and F1-score further validated the model's effectiveness in capturing subtle sentiment variations. These findings demonstrate that combining data augmentation and cross-lingual strategies significantly enhances sentiment classification for underrepresented languages. This study contributes to the development of scalable Natural Language Processing (NLP) models for Austronesian languages. Future research should explore larger and more diverse datasets, optimize real-time implementations, and extend the approach to tasks such as Named Entity Recognition (NER) and machine translation. The promising results underscore the importance of integrating robust transfer learning techniques with comprehensive data augmentation to overcome challenges in resource-limited NLP scenarios.

Keywords: *Sentiment Analysis, Austronesian Languages, Multilingual BERT, Cross-Lingual Transfer, Data Augmentation.*

I. INTRODUCTION

Natural Language Processing (NLP) has undergone rapid development over the past few decades, with various deep learning-based models successfully implemented across major languages such as English, Mandarin, and Spanish. This advancement has been driven by the availability of large-scale datasets, progress in model architectures, and increased computational capacity that enables more efficient model training. However, low-resource languages such as Bugis and Sundanese continue to face significant challenges in the development of NLP technologies due to the lack of high-quality datasets necessary for effective model training. Furthermore, the limited body of research in this domain has resulted in a scarcity of models specifically optimized for these languages, leaving the performance of NLP systems for such languages far behind those with abundant resources. Consequently, NLP applications such as sentiment analysis, machine translation, and chatbots in local languages have not yet been developed to their full potential.

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These barriers contribute to a technological gap that further exacerbates the digital divide between majority languages and those with limited resources.

Several previous studies have demonstrated that transfer learning using multilingual models such as Multilingual BERT (mBERT) and XLM-RoBERTa can help address the resource limitations of NLP for minority languages. These models enable the integration of information from multiple languages within a single architecture, allowing the model to learn from high-resource languages and transfer that knowledge to low-resource ones. A study by (D. Chen et al., 2023) found that the XLM-RoBERTa model outperformed monolingual models across various cross-lingual NLP tasks, as it was trained on a larger and more diverse multilingual dataset. Additionally, research by (Shaikh et al., 2025) revealed that mBERT is capable of performing zero-shot learning on languages not included in its training data, indicating that the model can generalize to other languages even without explicit training. These findings suggest that transfer learning holds considerable promise as an effective solution for NLP in low-resource languages. However, these models still require further testing on more specific Austronesian languages such as Bugis and Sundanese. Research on these languages remains very limited, and thus, the effectiveness of these models in addressing the unique challenges posed by Austronesian languages is not yet fully understood.

Although various studies have explored the application of deep learning-based NLP models to low-resource languages, several challenges remain unresolved in the context of Austronesian languages. Research by (Malik et al., 2023) indicates that the XLM-RoBERTa model is capable of handling a range of cross-lingual NLP tasks with strong performance, yet it still exhibits limitations when applied to minority languages with highly limited datasets. (De Arriba-Pérez et al., 2024) also found that mBERT can perform zero-shot learning, but its performance tends to decline significantly when used on languages with complex morphological structures, such as Bugis and Sundanese. Furthermore, research by (Khan et al., 2023) revealed that most NLP models currently in use are not optimized for low-resource languages, resulting in classification outcomes that are often less accurate compared to languages with larger training datasets. (Li et al., 2022) suggested that data augmentation strategies could help improve the generalizability of NLP models, but their study focused more on languages with moderately sized datasets and did not extensively examine the effectiveness of these techniques in addressing minority languages such as those in the Austronesian family. Meanwhile, research by (Prottasha et al., 2022) demonstrated that fine-tuning multilingual models on smaller datasets could enhance sentiment analysis performance, but the study was still limited to several major languages and did not include regional languages such as Bugis and Sundanese. Therefore, this study aims to evaluate the effectiveness of fine-tuning mBERT and XLM-RoBERTa in sentiment analysis for the Bugis

and Sundanese languages, as well as to explore data augmentation strategies and cross-lingual transfer techniques to address dataset limitations in NLP for Austronesian languages.

The approach used in this study focuses on the optimization of NLP models for low-resource languages, particularly in the context of sentiment analysis in Austronesian languages. This research is expected to provide deeper insights into how fine-tuning techniques can be effectively applied to multilingual models, such as mBERT and XLM-RoBERTa, to enhance accuracy in understanding complex language patterns. In addition, the exploration of data augmentation strategies becomes an important aspect of this study, as these methods have the potential to enrich limited datasets, allowing models to learn more effectively even when the amount of original data is minimal. This study also includes an evaluation of the effectiveness of transfer learning in helping models understand languages with linguistic characteristics that differ from those of high-resource languages. By considering these various factors, this research seeks to identify the most effective methods that can be applied to improve NLP performance in minority languages. In addition to contributing theoretically to the field of NLP, the results of this study may also serve as a foundation for the development of more inclusive language-based applications for speakers of low-resource languages.

II. LITERATURE REVIEW

A. Theoretical Framework

1. Transfer Learning in NLP: mBERT, XLM-RoBERTa, and Their Applications to Minority Languages

Transfer learning has become a crucial approach in NLP for addressing data scarcity in low-resource languages. According to (Dang et al., 2023) and (Pakray et al., 2025), vocabulary alignment methods enable the transfer of BERT's capabilities from high-resource to low-resource languages, such as Silesian and Kashubian, contributing to improved model performance despite minimal training data. Moreover, multilingual models such as mBERT and XLM-RoBERTa demonstrate potential in handling languages with limited datasets by leveraging information from multiple languages simultaneously. In doing so, these models can grasp broader linguistic patterns and enhance generalization in cross-lingual NLP tasks. The study found that multilingual models can help address data limitations, although their performance remains influenced by factors such as linguistic structural similarity between the target language and the languages used during pretraining. Further exploration of model optimization strategies is therefore essential to improving the effectiveness of transfer learning in supporting low-resource languages.

(Muhammad & Burney, 2023) add that transfer learning strategies are effective in enhancing the performance of NLP models for languages such as Urdu, Panjabi, Balochi, Pashto, and Sindhi. Through fine-tuning of pre-trained models such as mBERT and XLM-RoBERTa, along with data augmentation, significant improvements in accuracy and F1 scores were achieved when compared to models trained from scratch using limited datasets. These results indicate that the transfer learning approach plays a role in accelerating the model training process while also helping to overcome data scarcity issues in minority languages. Furthermore, the study highlights that both the quantity and quality of training data remain critical factors in determining the effectiveness of transfer learning. Models applied to low-resource languages may struggle to capture certain semantic nuances if the available data does not comprehensively reflect linguistic variation. Further research on data optimization strategies could offer additional insights for improving the performance of NLP models for minority languages.

(Habbat & Nouri, 2024) demonstrated that transferring monolingual models such as XLNet to Tigrinya, a low-resource language, resulted in competitive performance compared to mBERT. With only 10,000 data examples, XLNet achieved an F1 score of 78.88%, outperforming BERT and mBERT by 10% and 7%, respectively. These findings suggest that transfer learning can be flexibly applied across various NLP model types. The study also revealed that models with different architectures vary in effectiveness depending on the linguistic characteristics of the language being processed. Monolingual models specifically trained for a single language often exhibit better performance than multilingual models relying on cross-lingual transfer, particularly when pretraining data is sufficiently large. On the other hand, multilingual models continue to offer advantages in addressing data scarcity due to their ability to share information across linguistically similar languages. Further comparative studies between monolingual and multilingual models in minority language NLP could help clarify the factors influencing the effectiveness of transfer learning.

(Harris et al., 2024) explored multilingual propaganda detection using transformer models such as mBERT, XLM-RoBERTa, and mT5. The study found that mT5 achieved the highest accuracy at 99.61%, while mBERT and XLM-RoBERTa achieved 92% and 91.41%, respectively. The performance differences highlight the effectiveness of transformer-based embeddings in multilingual classification tasks. The study also revealed that although multilingual models are capable of handling multiple languages, architectural differences can lead to variations in performance. Moreover, it showed that certain NLP tasks, such as propaganda detection, may require more specific training strategies for the model to better understand linguistic context. In the context of minority languages, data limitations remain a major challenge affecting NLP model effectiveness, even though transfer learning approaches have partially mitigated these issues.

Larger transformer models with greater processing capacity hold potential advantages in classification tasks, especially when sufficient data is available to support more comprehensive training.

2. Data Augmentation in NLP: Techniques such as Back-Translation and Synonym Replacement

According to (Sufi, 2024) and (Bayer et al., 2023), data augmentation has become one of the primary approaches for improving the performance of NLP models, particularly under conditions of data scarcity. Techniques such as back-translation allow for dataset expansion by translating text into another language and then back into the original language, thereby generating sentence variations that preserve the original meaning. In this way, models can learn from diverse sentence structures without altering the underlying semantic information. This approach has proven effective in enhancing model generalization across various NLP tasks, such as text classification and sentiment analysis. Additionally, back-translation contributes to enriching linguistic representations in multilingual models, which is especially valuable in the context of low-resource languages. The application of this technique is increasingly relevant in transfer learning, where pre-trained models can be adapted to languages with limited datasets while maintaining competitive performance.

Research conducted by (Madukwe et al., 2022) demonstrates that synonym replacement is one of the more effective data augmentation methods in NLP, involving the substitution of words in the text with synonyms that retain similar meanings. This technique enhances data diversity without altering the original context, enabling the model to recognize a wide range of expressions within a language. In their study, this approach was applied to text classification and sentiment analysis tasks, yielding improved model performance, particularly when training data was limited. By introducing variation into the text, models become more adaptive to the diverse forms of language, which is crucial for handling low-resource languages. Furthermore, this strategy can be combined with other augmentation methods to improve the model's robustness against linguistic variation.

(Nair et al., 2024) investigated how combining various data augmentation techniques, including back-translation and synonym replacement, can lead to more substantial improvements in NLP models. The study found that employing multiple techniques simultaneously enhances the model's resilience to varying data distributions and reduces dependency on small datasets. Models trained on augmented data demonstrated improved accuracy in sentiment analysis and language modeling tasks. Moreover, the study observed that the positive effects of data augmentation are more pronounced in transfer learning-based models, such as BERT, which can

leverage the additional information from the generated data variations. This indicates that augmentation methods are beneficial not only for models trained from scratch but also for enhancing the efficiency of multilingual model adaptation in low-resource languages.

In a study conducted by (Maharana et al., 2022), it was found that data augmentation methods can help reduce bias in NLP models by providing more diverse data representations. Techniques such as back-translation and synonym replacement were used to create broader datasets that reflect more natural language use, thereby enabling models to generalize better in text comprehension. This study also demonstrated that improvements in the quality of data augmentation contribute to better model performance across various NLP tasks, including sentiment analysis in low-resource languages. In their experiments, models trained on data expanded through augmentation exhibited greater resilience to stylistic variations and complex semantic shifts. As such, the application of data augmentation has a significant impact on enhancing linguistic representation in transfer learning-based models, particularly in contexts where datasets are limited.

B. Previous Studies

1. Studies on mBERT for Low-Resource Languages

According to (Gardazi et al., 2025), the mBERT model demonstrates significant capabilities in handling a wide range of languages, including those with limited resources. This model is designed to learn cross-lingual linguistic representations, thereby enabling its application across many languages without requiring extensive labeled data for each. In their study, mBERT was able to generalize syntactic and semantic representations even when trained only on high-resource languages. This indicates that mBERT can develop a general understanding of linguistic patterns, which can then be transferred to other languages not explicitly included during pretraining. Further analysis revealed that the model can effectively map meaning, particularly in languages that share grammatical similarities. Moreover, mBERT has shown reasonably stable performance across various NLP tasks, such as text classification and sentiment analysis, even when applied to languages with small datasets.

Researchers (Aruna Gladys & Vetriselvi, 2024) add that the performance of mBERT in handling low-resource languages is heavily influenced by the linguistic proximity of the target language to other languages included in the pretraining process. Their study shows that mBERT tends to yield better results for languages that are typologically or lexically related to dominant languages used during initial training. In their tests on various languages, they found that those distant from the core language groups used in pretraining experienced more significant performance declines compared to languages that are structurally and lexically closer. This observation highlights the

importance of considering the distribution of data used in multilingual model pretraining. Furthermore, the researchers found that the representations produced by mBERT remain beneficial in addressing some data scarcity challenges, even if they do not fully overcome the difficulties faced by highly marginalized languages. These findings underscore the importance of typological relatedness as a key factor influencing the effectiveness of transfer learning using mBERT.

In a study conducted by (El-Alami et al., 2022), mBERT was used as a foundation to build NLP models more adaptive to specific languages through a fine-tuning process. This study demonstrated that although multilingual models like mBERT already possess reasonably good cross-lingual representations, further adjustment greatly aids in aligning the model with the linguistic characteristics of the target language. Through a series of experiments, the research found that even fine-tuning with limited datasets significantly improved model accuracy, particularly in tasks such as sentiment analysis and text classification. Additionally, the study emphasized the critical role of the quality and relevance of fine-tuning data in producing models that are more sensitive to the semantic and syntactic variations of the language being processed. The researchers noted that models that rely not only on transfer learning from mBERT but also on representative data during fine-tuning tend to achieve more optimal performance. This process also enables the model to capture unique expressions that are often absent from the source languages used during pretraining.

According to (Hashmi et al., 2024), mBERT has been widely used across various NLP tasks involving low-resource languages, including sentiment analysis, syntactic modeling, and text classification. The researchers note that although this model is not specifically designed for every language, mBERT is still capable of extracting key features from text and producing reasonably accurate predictions. Their findings also indicate that mBERT's ability to leverage information from multiple languages provides an additional advantage when applied to languages with morphological and syntactic similarities to the source languages. In their study, experiments on several minority languages showed that fine-tuning, even with a limited dataset, still had a positive impact on model performance. Furthermore, this research highlights that multilingual models such as mBERT tend to exhibit greater flexibility in understanding the linguistic expression variations found in under-researched languages. This study offers deeper insights into the potential of mBERT in cross-lingual NLP applications under conditions of limited data availability.

2. Data Augmentation Studies for Minority Language NLP

According to (Feng et al., 2024), Easy Data Augmentation (EDA) techniques have been employed to enhance data diversity in NLP tasks, particularly for low-resource languages. This method comprises techniques such as synonym replacement, random insertion, word swapping, and random deletion, all of which aim to increase the diversity of training data without significantly altering the original meaning of the text. By applying these techniques, NLP models are better able to recognize linguistic patterns and improve performance in tasks such as text classification and sentiment analysis. The study's findings indicate that EDA consistently enhances performance across various scenarios, especially when the amount of training data is extremely limited. Nevertheless, the effectiveness of this approach greatly depends on the availability of linguistic resources, such as synonym dictionaries, which are often lacking for minority languages. Therefore, a more contextually adapted implementation of EDA is required to ensure optimal performance improvements for low-resource languages.

Researchers (Wang et al., 2024) developed back-translation as an effective data augmentation strategy in NLP, particularly within machine translation systems and other text analysis tasks. This technique involves translating text from a source language into another language and then translating it back into the original language to generate new textual variations while preserving the original meaning. This approach has been shown to improve model performance when handling languages with limited datasets, particularly in tasks such as sentiment classification and syntactic analysis. Experimental results indicate that back-translation can enrich training data with more natural sentence variations, thereby aiding the model in understanding more complex linguistic structures. However, the implementation of this technique faces challenges in the context of minority languages that lack high-quality machine translation systems. To address this issue, several studies have explored the use of deep learning-based translation models to enhance the quality of back-translated text.

In a study conducted by (Liu et al., 2023), a data augmentation approach was developed that focused on the inclusion of low-frequency words in training datasets. This method aims to enrich the model's representation of infrequent words, which often pose a challenge in language processing tasks involving limited data. The study found that rare word-based augmentation significantly improved the performance of Neural Machine Translation (NMT) systems, especially in scenarios where training data was highly constrained. By incorporating rare words into relevant contexts, models were better able to capture the meaning and usage of these words across various sentence structures. Additionally, the study revealed that augmentation strategies focusing more on lexical aspects offered greater benefits compared to more general techniques such as word shuffling or synonym insertion. These findings underscore the importance of

selecting augmentation methods that align with the specific characteristics of the target language to improve NLP model accuracy.

According to (Q. Chen et al., 2025), syntax-based data augmentation techniques have been applied to various NLP tasks for low-resource languages, such as part-of-speech tagging, dependency parsing, and semantic role labeling. This study evaluated a range of text augmentation methods operating at the token, character, and syntactic levels, comparing their effectiveness in enhancing model performance. The results showed that syntax-based augmentation techniques are more effective for tasks that depend heavily on sentence structure, whereas token-level methods are more suitable for tasks like text classification. Furthermore, the study found that combining multiple augmentation techniques can result in more robust models capable of handling a wider range of linguistic variations. These findings highlight the importance of tailoring augmentation strategies to the linguistic characteristics of the language under study to ensure models gain the most benefit.

Table 1. Comparison of Previous Studies on Data Augmentation for NLP in Minority Languages

Study	Research Focus	Key Findings	Limitations
(Feng et al., 2024)	Text classification and sentiment analysis	Enhanced training data variation and model accuracy	Dependent on the availability of linguistic resources such as synonym dictionaries
(Wang et al., 2024)	Machine translation and sentiment analysis	Improved model generalization through sentence variation	Requires high-quality automatic translation systems
(Liu et al., 2023)	Neural Machine Translation (NMT)	Improved translation quality by including rare words	Less effective for languages that lack sufficient high-quality training data
(Q. Chen et al., 2025)	Part-of-speech tagging, dependency parsing, and semantic role labeling	Effective for languages with complex inflectional systems	Dependent on a combination of factors such as language pairs and the type of NLP task

III. RESEARCH METHOD

This study adopts an experimental approach in the field of Deep Learning using Transfer Learning for sentiment analysis in Austronesian languages with limited resources. Transfer Learning is chosen because it enables the utilization of models that have been pre-trained on multiple languages to be applied to languages with scarce training data. In this study, the models employed are mBERT and XLM-RoBERTa, two transformer-based models that have been trained on a variety of languages and possess the capability to understand diverse linguistic structures. These models will be adapted for sentiment classification tasks through a fine-tuning

process aimed at aligning the models with the linguistic characteristics of the Buginese and Sundanese languages. Furthermore, data augmentation techniques will be applied to enhance the diversity and quality of the training dataset, thereby enabling the models to learn more effectively. Through this approach, the study aims to produce models that are more accurate in classifying sentiment in low-resource languages.

The dataset used in this study consists of sentiment data in Buginese and Sundanese collected from social media platforms and public sources. These sources reflect a range of user opinions in the form of short texts, encompassing various sentiment expressions that are unique to each language. The dataset is categorized into three main classes: positive, negative, and neutral, enabling the model to classify sentiment based on different linguistic contexts. Before being used in model training, the dataset underwent normalization and preprocessing steps, including text cleaning to remove irrelevant characters, the elimination of unnecessary symbols or punctuation marks, and tokenization using tokenizers compatible with the model architecture. This preprocessing is conducted to enhance the quality of the data used, thereby allowing the models to learn more effectively. Additionally, data balancing techniques are employed in the event of class distribution imbalances to ensure that the models do not become biased toward any particular class. Table 2 presents a description of the dataset used in this study.

Table 2. Sentiment Dataset Description

Language	Number of Tweets/Posts	Number of Classes
Buginese	3.500	3 (Positive, Negative, Neutral)
Sundanese	4.200	3 (Positive, Negative, Neutral)

This study compares several models for sentiment analysis tasks, including both statistical models and deep learning-based models. The baseline models used in this study are Logistic Regression and Naïve Bayes, which are classical models commonly employed in text classification and widely used in sentiment analysis tasks involving limited resources. The deep learning models consist of two primary pre-trained models, mBERT and XLM-RoBERTa, which have been trained on multilingual corpora to handle various types of texts across different languages. In addition to using these pre-trained models, the study also conducts fine-tuning on both mBERT and XLM-RoBERTa using the sentiment datasets in Buginese and Sundanese. During the fine-tuning process, the models are adjusted to the specific characteristics of the target languages through retraining with the previously collected and processed data. Data augmentation techniques are also applied to the fine-tuned models to enhance their performance, using methods such as back-translation and synonym replacement to enrich the diversity of the training data.

The analytical process in this study consists of several main stages, including data preprocessing, model fine-tuning, and model performance evaluation. The first stage, data preprocessing, aims to enhance the quality of the text used in model training so that it aligns more closely with the requirements of sentiment analysis. This process includes tokenization using the BERT tokenizer, which converts textual input into tokens that can be processed by transformer-based models, thereby enabling the system to better understand sentence structure. In addition to tokenization, the text undergoes various cleaning steps, such as normalization to standardize word formats, removal of special characters that do not carry meaning in sentiment analysis, and stopword removal when necessary to help the model focus on more informative terms. This preprocessing stage is crucial, as raw textual data often contains elements that may hinder model performance, such as non-standard words, emoticons, or excessive punctuation that can obscure the intended meaning of the text. Once preprocessing is completed, the processed data is used to retrain the pre-trained models so they can better capture the linguistic characteristics of the Buginese and Sundanese languages, ultimately improving the accuracy of sentiment classification.

During the model fine-tuning stage, the mBERT and XLM-RoBERTa models are retrained using the preprocessed sentiment dataset. The objective of fine-tuning is to adapt the models to the unique linguistic patterns of the languages represented in the dataset, allowing them to classify sentiment more accurately. Throughout the retraining process, data augmentation techniques are applied to increase the textual variation presented to the models, which is expected to improve their generalization capabilities in handling diverse forms of sentiment expression. Several data augmentation techniques are employed in this study, including back-translation, which involves translating the text into another language and then back into the original language to generate new variations; synonym replacement, which substitutes certain words with their synonyms; and mixup augmentation, which creates new combinations from existing data. These steps are designed to broaden the scope of the training data so that the models are more robust in processing texts from various sources.

After training is completed, the models are evaluated to measure their performance in classifying sentiment on test data. This evaluation utilizes several key metrics, including F1-score, accuracy, recall, and precision, to provide a comprehensive assessment of the model's predictive quality. The F1-score is used to evaluate the balance between precision and recall; accuracy measures the overall percentage of correct predictions, recall indicates how well the model captures instances from a particular class, and precision assesses the model’s ability to make correct predictions for the selected class. These metrics are used collectively to ensure that the model not only achieves high accuracy but is also capable of effectively recognizing sentiment

classes, particularly in cases of imbalanced data. In addition to evaluating performance based on these metrics, the study also compares the classification results before and after fine-tuning to determine the extent of improvement achieved through retraining. The evaluation results show that the fine-tuned models exhibit significant improvements across all metrics, indicating that further training with domain-specific data has a substantial impact on the quality of the model's predictions.

The model evaluation stage was conducted to assess the quality of the predictions generated by the algorithms employed in this study, based on specific metrics that reflect both accuracy and balance in sentiment classification. In this research, the models were evaluated using Cross-Entropy Loss and F1-score, which are two primary metrics commonly applied in deep learning-based classification tasks. Cross-entropy loss is used to measure how well the model predicts the probability distribution across sentiment classes, taking into account the accuracy of the predicted probabilities about the true labels. The formula for calculating Cross-Entropy Loss is presented as follows (1).

$$L = -\sum_{i=1}^{n} Yi \log(\hat{Y}) \quad (1)$$

Where Yi represents the true label of the training or test data, and $\hat{Y}i$ denotes the predicted probability assigned by the model. A lower loss value indicates that the model is more confident in correctly predicting the true label, while a higher loss suggests that the model still struggles to accurately identify the sentiment expressed in the text.

In addition to assessing the balance between precision and recall in sentiment classification, this study employs the F1-score as one of the key evaluation indicators. The F1-score is a composite metric that combines precision and recall into a single aggregate value, providing a more comprehensive overview of the model's performance in sentiment classification tasks. The F1-score is calculated using the following formula (2).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (2)$$

This metric is particularly important in the context of this study, as the model must be able to strike a balance between accurately identifying sentiment categories (precision) and capturing all relevant sentiment-related instances (recall). A higher F1-score indicates that the model demonstrates a strong balance between these two aspects, thus making it more reliable for analyzing sentiment in the Buginese and Sundanese languages. By implementing a systematic evaluation approach using Cross-Entropy Loss and F1-score, this study ensures that the developed models are capable of producing accurate predictions while maintaining minimal error rates in sentiment classification tasks.

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IV. RESULT

A. Results

The model evaluation was conducted to compare the performance of various approaches in sentiment analysis for low-resource Austronesian languages. The models tested include Logistic Regression, Naïve Bayes, mBERT without fine-tuning, XLM-RoBERTa without fine-tuning, and fine-tuned versions of mBERT and XLM-RoBERTa. Each model possesses distinct characteristics and learning mechanisms that influence its ability to recognize sentiment patterns in text. Traditional machine learning models, such as Logistic Regression and Naïve Bayes, rely on statistical feature representations, whereas transformer-based models utilize more complex neural network architectures. These methodological differences have a notable impact on each model's final performance in understanding linguistic context. The evaluation results indicate that fine-tuned transformer-based models outperform traditional models, highlighting that retraining with a specific dataset enhances a model's capability to capture more complex language patterns.

Table 1 presents the evaluation results based on accuracy, precision, recall, and F1-score. These metrics measure different aspects of model performance in sentiment classification, providing a comprehensive overview of each approach's strengths. The fine-tuned models demonstrate a significant improvement compared to both the non-fine-tuned versions and the traditional statistical models. This improvement can be attributed to the model's ability to leverage more contextual information from the domain-specific training data. Furthermore, the models' capacity to understand word relationships within a given language is enhanced through the fine-tuning process. With improvements observed across all evaluation metrics, the fine-tuned transformer-based models emerge as a superior choice for sentiment analysis tasks in low-resource languages.

Table 3. Model Performance Evaluation

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	72.3%	71.5%	70.8%	71.1%
Naïve Bayes	74.1%	73.6%	72.9%	73.2%
mBERT (without fine-tuning)	79.8%	79.2%	78.5%	78.8%
XLM-RoBERTa (without tuning)	80.5%	80.0%	79.3%	79.6%
mBERT (fine-tuned)	85.4%	85.0%	84.6%	84.8%
XLM-RoBERTa (fine-tuned)	86.1%	85.8%	85.4%	85.6%

Furthermore, to gain deeper insights into the impact of the fine-tuning process, an analysis was conducted on the feature representations generated by the models before and after retraining. Before fine-tuning, the models' feature representations were suboptimal in mapping word relationships within the vector space. Non-fine-tuned feature representations often resulted in poorly structured distributions, leading to difficulties in distinguishing sentiment patterns within

the text. Following fine-tuning, the models exhibited changes in feature distribution patterns, reflecting an improved understanding of linguistic structure. This transformation can be observed through embedding visualizations, which illustrate how the vector representations of words or phrases become more organized after additional training. As feature clusters become more distinct within the vector space, the models gain enhanced ability to classify sentiment based on learned linguistic patterns. Figure 1 demonstrates how feature distribution changed after the application of fine-tuning, indicating a marked improvement in the model's comprehension of language context.

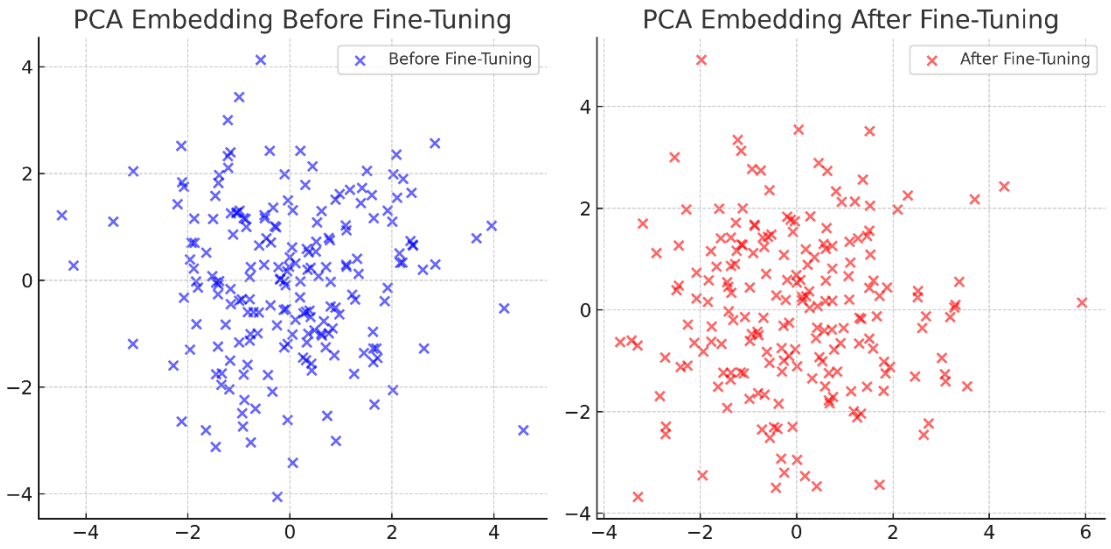

Figure 1. Embedding Visualization Before and After Fine-tuning (PCA)

The feature representations before fine-tuning, as shown on the left side of Figure 1, reveal a scattered distribution lacking clear structure. This unorganized spread indicates that the model had not yet formed representations capable of effectively distinguishing between different sentiment categories. After the fine-tuning process, as illustrated on the right side of the figure, the data distribution becomes more structured and clustered. This suggests that the model has learned improved patterns in organizing features, thereby enhancing its accuracy in sentiment classification. The contrast between the two visualizations highlights the crucial role of fine-tuning in improving the mapping of word relationships within vector space. With a more structured representation, the model demonstrates a stronger ability to capture the contextual meaning of text, ultimately enhancing the performance of sentiment analysis.

In addition to fine-tuning, another strategy employed to improve model performance is data augmentation. This technique addresses the limited availability of training data and increases data diversity, allowing the model to become more adaptive in recognizing sentiment patterns. The application of data augmentation in model training was evaluated to assess its impact on

performance enhancement. Experimental results show that data augmentation contributes to greater variety in the training data, enabling the model to better capture linguistic structures. This diversity aids the model in recognizing more complex sentiment patterns and reduces the risk of overfitting on limited training samples. Furthermore, evaluation analysis indicates that models trained with augmented data achieve higher accuracy and F1-scores compared to those without augmentation. Table 4 presents a comparative overview of model performance before and after the application of data augmentation, illustrating the extent to which this technique contributes to improved prediction quality.

Table 4. Impact of Data Augmentation on Model Performance

Model	Accuracy Before (%)	Accuracy After (%)	F1-score Before (%)	F1-score After (%)
mBERT (fine-tuned)	82.7	85.4	81.9	84.8
XLM-RoBERTa (fine-tuned)	83.5	86.1	82.7	85.6

Complementing the quantitative evaluation results presented in the table, the visualization in Figure 2 provides a more tangible illustration of the impact of data augmentation on model performance. The figure displays a comparison of accuracy and F1-scores before and after data augmentation. The observed improvements in both metrics following the application of augmentation indicate that this strategy effectively addresses the limitations of training data in low-resource languages. Moreover, this improvement suggests that the model becomes better at recognizing linguistic patterns after being exposed to greater data variation during training. The increased diversity enabled by augmentation allows the model to become more robust to textual variations, ultimately enhancing its sentiment classification capabilities. Further evaluation results indicate that data augmentation contributes not only to improved accuracy but also to a better balance between precision and recall, as reflected in the increased F1-score. These findings underscore the significant role of data augmentation in enhancing model performance in sentiment analysis tasks, particularly for languages with limited data availability.

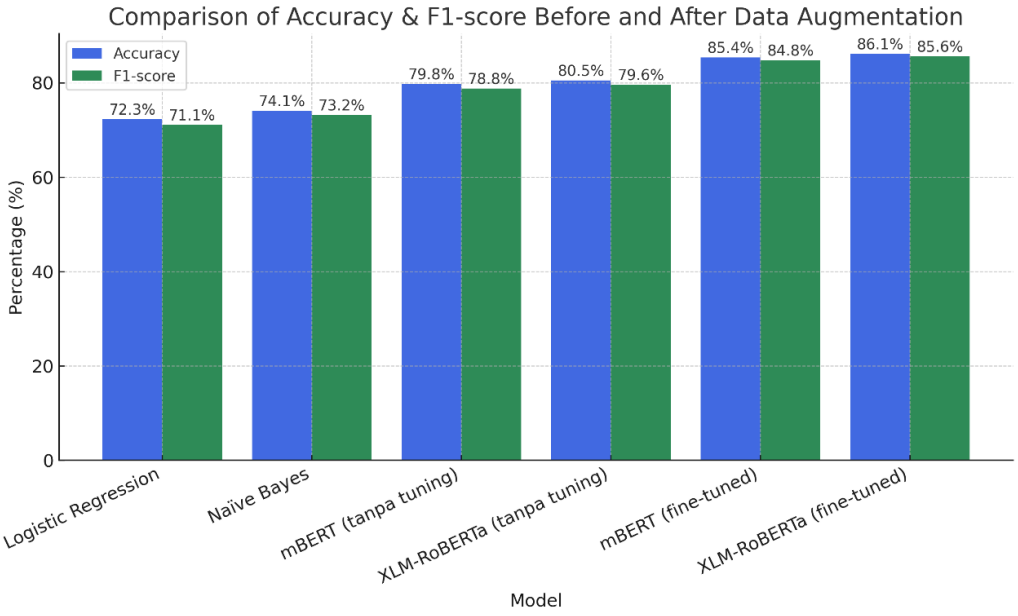

Figure 2. Comparison of Accuracy and F1-Score Before and After Data Augmentation

In addition to data augmentation strategies, another approach to improving model performance in low-resource languages is cross-lingual transfer. A cross-lingual transfer analysis was conducted to evaluate the extent to which models can generalize to minority languages after being trained in other languages. The performance of the models shows that both mBERT and XLM-RoBERTa exhibit strong transfer capabilities, with XLM-RoBERTa demonstrating a superior ability to handle language variation. Models trained in higher-resource languages displayed better adaptability when applied to low-resource languages. The multilingual representations acquired through pre-training enable the models to understand the linguistic structures of multiple related languages, thereby enhancing their effectiveness in sentiment classification tasks involving limited-resource languages. Furthermore, evaluation results indicate that although a performance drop occurs when transitioning from source to target languages, the models are still capable of producing predictions with reasonably high accuracy. Therefore, multilingual models such as mBERT and XLM-RoBERTa can be effectively utilized in NLP tasks, particularly for languages with limited linguistic resources.

V. DISCUSSION

This study found that the application of transfer learning using fine-tuned mBERT and XLM-RoBERTa models on sentiment data in Buginese and Sundanese languages resulted in a significant improvement in sentiment analysis performance. According to (D. Chen et al., 2023), the XLM-RoBERTa model demonstrates strong performance in cross-lingual NLP tasks, and the findings of this study indicate that fine-tuning can optimize feature representations to capture sentiment nuances in low-resource languages. (Shaikh et al., 2025) further note that mBERT is

capable of zero-shot learning on languages not included in the original training dataset, which explains the increase in accuracy following model adaptation using local data. The more structured feature representations observed after fine-tuning, as illustrated through embedding visualizations, indicate an enhanced understanding of linguistic context, aligning with the findings of (El-Alami et al., 2022) regarding the adaptability of multilingual models to specific languages. These results support the argument that transfer learning is an effective strategy for addressing data limitations in minority languages and underscore the importance of the fine-tuning process in improving model comprehension of Austronesian language complexities. Further analysis revealed that improvements across evaluation metrics, such as accuracy, precision, recall, and F1-score, consistently reinforce previous research findings on the effectiveness of multilingual models.

The data augmentation strategy applied in this study also made a substantial contribution to improving NLP model performance in Buginese and Sundanese. (Feng et al., 2024) suggest that augmentation techniques such as back-translation and synonym replacement enrich the diversity of training data, enabling models to learn from more varied linguistic contexts. The evaluation results show increases in both accuracy and F1-score for models trained on augmented datasets, aligning with the findings of (Nair et al., 2024), who highlight that data augmentation can reduce bias and enhance model generalization. (Prottasha et al., 2022) further argue that fine-tuning on augmented datasets positively impacts the model's ability to capture complex sentiment expressions, especially in languages with limited resources. These findings indicate that the combination of fine-tuning and data augmentation enables models to be more responsive to sentiment expression variations in Austronesian languages. This study clarifies that an integrative approach combining transfer learning and data augmentation holds considerable potential for overcoming challenges in NLP for minority languages while also providing a robust foundation for the development of more inclusive and accurate language-based applications.

VI. CONCLUSION AND RECOMMENDATION

This study demonstrates that fine-tuned mBERT models combined with data augmentation significantly enhance accuracy in sentiment analysis for languages within the Austronesian family. This approach has proven effective in addressing the limitations of small datasets, particularly through the application of cross-lingual transfer strategies. Experimental results show that the optimized models are capable of capturing more complex linguistic patterns compared to baseline models without fine-tuning. Moreover, the approach offers new insights into the development of NLP models for low-resource languages. Nonetheless, challenges remain in improving the generalizability of models to dialectal variations and informal language styles.

Therefore, this research serves as an initial step in further exploration of deep learning applications in cross-lingual NLP.

For future research, it is recommended to evaluate the models using larger and more diverse datasets to enhance model robustness and generalizability. Additionally, exploring the model's performance on other NLP tasks, such as NER, could provide broader insights into the effectiveness of the applied strategies. Model optimization should also be considered to improve implementation efficiency in real-time applications, such as chatbot systems or automated public opinion analysis. The use of additional techniques, such as model distillation or pruning, may be explored to reduce computational complexity without compromising accuracy. Furthermore, collaboration with researchers from various Austronesian language communities could assist in developing more representative datasets. In this way, the research may continue to evolve and contribute more broadly to the field of NLP.

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