**Javanese Hate Speech Detection with Improved Training Strategy: Achieving 86.98% Accuracy through Focal Loss and Class Balancing**

Mukhlis Amien1

Department of Informatics, Universitas Bhinneka Nusantara, Malang, East Java, Indonesia1

E-mail: amien@ubhinus.ac.id1

# **Abs**t**ract**

This research proposes a novel framework for hate speech detection in Javanese, a low-resource language with over 80 million speakers that remains underrepresented in Natural Language Processing (NLP) technologies. Existing models, predominantly trained on high-resource languages like English, often fail to capture the sociolinguistic nuances and implicit forms of hatred prevalent in the Javanese cultural context (Saputri et al., 2021). This limitation stems from a lack of understanding of local politeness rules, known as unggah-ungguh basa (Setiawan, 2020). To bridge this gap, we introduce a BERT-based architecture (Devlin et al., 2019) that embeds local wisdom via a Multi-Task Learning (MTL) approach. The model is trained to perform two tasks simultaneously: hate speech classification and politeness level classification based on unggah-ungguh norms (Kusuma et al., 2021). This auxiliary task compels the model to learn sociopragmatic features that inform the primary task, enabling it to identify implicit hate speech through politeness violations. The framework includes a culturally sensitive data curation strategy, an iterative dataset refinement process inspired by adversarial dataset creation techniques (Röttger et al., 2021), and a robust evaluation methodology. By embedding cultural concepts into deep learning, this research provides a replicable blueprint for creating culturally aware AI systems for other low-resource languages worldwide.

Keywords: Hate speech detection, Javanese language, IndoBERT, class imbalance, multilingual NLP

# Introduction

The proliferation of hate speech in Indonesia's digital space poses a significant threat to its diverse social fabric, with a notable increase in reported cases (Setiawan, 2020). While legal frameworks like UU ITE address the proliferation of hate speech, its linguistic manifestations are complex, ranging from explicit insults to subtle forms (Saputri et al., 2021). Developing automated detection systems is crucial, yet existing AI models, largely trained on high-resource Western languages, prove inadequate for languages like Javanese.

Despite having over 80 million speakers, Javanese is considered a low-resource language in NLP due to a scarcity of structured digital data and its inherent linguistic complexities, such as the intricate unggah-ungguh basa politeness system and prevalent code-switching. This research addresses the fundamental problem of how to computationally integrate abstract local wisdom, specifically *unggah-ungguh*, into a BERT-based architecture to create a more accurate and contextually aware hate speech detection model for Javanese.

Our objectives include developing a nuanced Javanese hate speech taxonomy, proposing an innovative Multi-Task Learning framework that simultaneously classifies hate speech and politeness levels, outlining culturally sensitive data strategies, and providing a replicable blueprint for culturally aware NLP systems in other low-resource contexts. This work aims to contribute a novel framework that operationalizes cultural concepts into machine learning, enabling the detection of implicit, context-dependent hate speech, and fostering a more ethical and decolonized approach to AI development.

# 2. Background

Despite the global recognition of the urgency of hate speech detection, the development of Artificial Intelligence (AI) solutions, particularly in Natural Language Processing (NLP), faces fundamental challenges when applied to contexts outside the dominance of English and Western cultures (Saputri et al., 2021). The main thesis of this research is that generic AI models, often trained on massive English-language data corpora reflecting Western cultural norms, are inherently inadequate for handling the linguistic and cultural complexities embedded in languages like Javanese. Recent studies show that even advanced multilingual models like mBERT and XLM-ROBERTa, designed for cross-lingual understanding, often exhibit degraded performance when applied to regional languages in Indonesia. These models struggle to cope with common linguistic phenomena in everyday Indonesian communication, such as code-switching, where speakers seamlessly switch between Indonesian, regional languages (like Javanese), and English within a single utterance.

This failure is not merely a technical issue but is rooted in what can be termed 'cultural bias' within these models. These models often lack sufficient training data and, more importantly, the contextual knowledge necessary to accurately interpret meaning in non-Western cultures. Javanese becomes a highly relevant case study in this regard. Although spoken by over 80 million people and thus one of the most widely spoken languages globally, Javanese is categorized as a 'low-resource language' in the NLP domain. This paradox highlights that "low-resource" status is not determined by the number of speakers, but by the scarcity of structured and annotated NLP resources, such as treebanks, clean large-scale corpora, and labeled datasets for specific tasks like hate speech detection (Setiawan, 2020). This gap creates a dilemma: the need for sophisticated detection systems is very high, but the tools and data to build them are very limited. Therefore, an approach that relies solely on applying larger or stronger models to existing data is a flawed strategy. Such an approach fails to address the root cause, which is the fundamental mismatch between the cultural assumptions embedded in generic AI models and the high-context communication norms prevalent in Javanese society. Genuine innovation requires redesigning the model's learning objectives to be explicitly aware of the underlying cultural framework.

# 3. Related Works

The development of sophisticated Natural Language Processing (NLP) systems for low-resource languages like Javanese heavily relies on advancements in **pre-trained language models and transfer learning**. Javanese, despite its large number of speakers, faces significant challenges due to the scarcity of structured digital resources, including annotated datasets for hate speech and domain-specific raw text corpora, particularly for informal social media language.

Current state-of-the-art NLP models, primarily based on the **Transformer architecture** (e.g., BERT, RoBERTa), are initially pre-trained on vast text data to learn general language representations, which are then fine-tuned for specific downstream tasks. While multilingual models like **mBERT and XLM-RoBERTa** offer cross-lingual understanding, they often show decreased performance on specific regional languages like Javanese. This limitation stems from their struggle with phenomena such as code-switching and their lack of deep cultural contextual knowledge, particularly concerning the nuanced politeness norms of Javanese (unggah-ungguh basa) which can convey implicit hate (Kusuma et al., 2021).

To address these shortcomings, researchers have developed models specifically for Indonesian, such as **IndoBERT** and its social media-adapted variant, **IndoBERTweet**, which demonstrate superior performance in their respective domains. Furthermore, specialized monolingual models like **Javanese BERT** have emerged, showing improved understanding of Javanese lexicon and syntax, though often limited by the formality of their training data. Models like **IndoJavE** also attempt to handle code-mixed data common in real-world scenarios.

Our proposed approach, which aims to integrate Javanese local wisdom like *unggah-ungguh basa* into a BERT-based architecture using a Multi-Task Learning (MTL) framework, builds upon these existing advancements. By adapting a strong base model to general Javanese text and then fine-tuning it on a hate speech detection task with an auxiliary task of politeness classification, our work aims to explicitly embed the cultural nuances that generic and even some specialized multilingual models miss This strategy seeks to enhance the model's ability to interpret subtle and context-dependent forms of hate speech in Javanese, addressing a critical gap identified in current NLP systems for culturally rich, low-resource languages.

# 4. Methodology

Our methodology is designed to address the challenges of class imbalance, cultural specificity, and robustness in Javanese hate speech detection. The process combines culturally informed dataset construction, a transformer-based model architecture, and optimized training strategies.

The evaluation was conducted on a balanced test set of 4,993 samples (~20% of the dataset). The complete dataset initially contained 24,964 entries; through augmentation, this number was increased to 32,452, yielding an approximately uniform class distribution (~8,113 instances per class). Preprocessing included text normalization, model-specific tokenization, and the application of class weighting during training.

To construct a culturally sensitive dataset, we adopted an iterative, **human-and-model-in-the-loop** approach inspired by dynamic data generation for hate detection. The original dataset, comprising ~40,000 entries curated across four annotation rounds, contained ~15,000 challenging perturbations and a hate-speech proportion of 54%, substantially higher than comparable corpora. Each instance was labeled not only for hate intensity but also for type (e.g., derogation, animosity, dehumanization, or support for hateful entities).

For the Javanese adaptation, all entries were translated and re-annotated according to a four-level severity taxonomy:

1. Bukan Ujaran Kebencian (Not Hate Speech): This category indicates content that is determined not to be hate speech.
2. Ujaran Kebencian Ringan (Mild Hate Speech): This refers to content that contains subtle or less severe forms of hate speech, possibly expressed indirectly or through minor violations of politeness norms.
3. Ujaran Kebencian Sedang (Moderate Hate Speech): This includes content with a noticeable degree of hateful intent, but perhaps not overtly aggressive or threatening.
4. Ujaran Kebencian Berat (Severe Hate Speech): This encompasses highly explicit, aggressive, and threatening hate speech, potentially involving direct insults, dehumanization, or incitement to violence.

This granular classification, adapted from a hierarchical taxonomy that aims for a balance between granularity and conceptual distinctiveness, allows for a more nuanced understanding of hate speech in Javanese, particularly considering the sociopragmatic rules of *unggah-ungguh*. The original dataset also categorized hate speech into types such as Derogation (explicit attacks), Animosity (implicit abuse), threatening language, Support for hateful entities, and Dehumanization. We will adapt these categorizations to fit the Javanese context and the four levels of hate speech severity.

# 4.1 Model Architecture

The backbone of our system is **IndoBERT Large v1.2**, a 340M-parameter transformer pre-trained on large-scale Indonesian corpora, which demonstrates transferability to Javanese. The architecture consists of 24 transformer layers, 1024 hidden dimensions, and 16 self-attention heads.

To adapt the model for hate speech detection, we appended a task-specific classification head with a 0.1 dropout rate. The model performs four-way classification aligned with the severity taxonomy described above.

# 4.2 Training Strategy

To address class imbalance and improve convergence, we employed a combination of training enhancements:

* Class Rebalancing: Stratified sampling ensured proportional representation of categories during each epoch.
* Class Weighting: Loss function weights were adjusted to penalize misclassifications of minority classes more heavily.
* Focal Loss: Introduced to further emphasize hard-to-classify examples and reduce bias toward majority classes.

Together, these techniques improved stability and reduced the dominance of the non-hate class, a common issue in imbalanced hate speech datasets.

# 4.3 Ablation Study

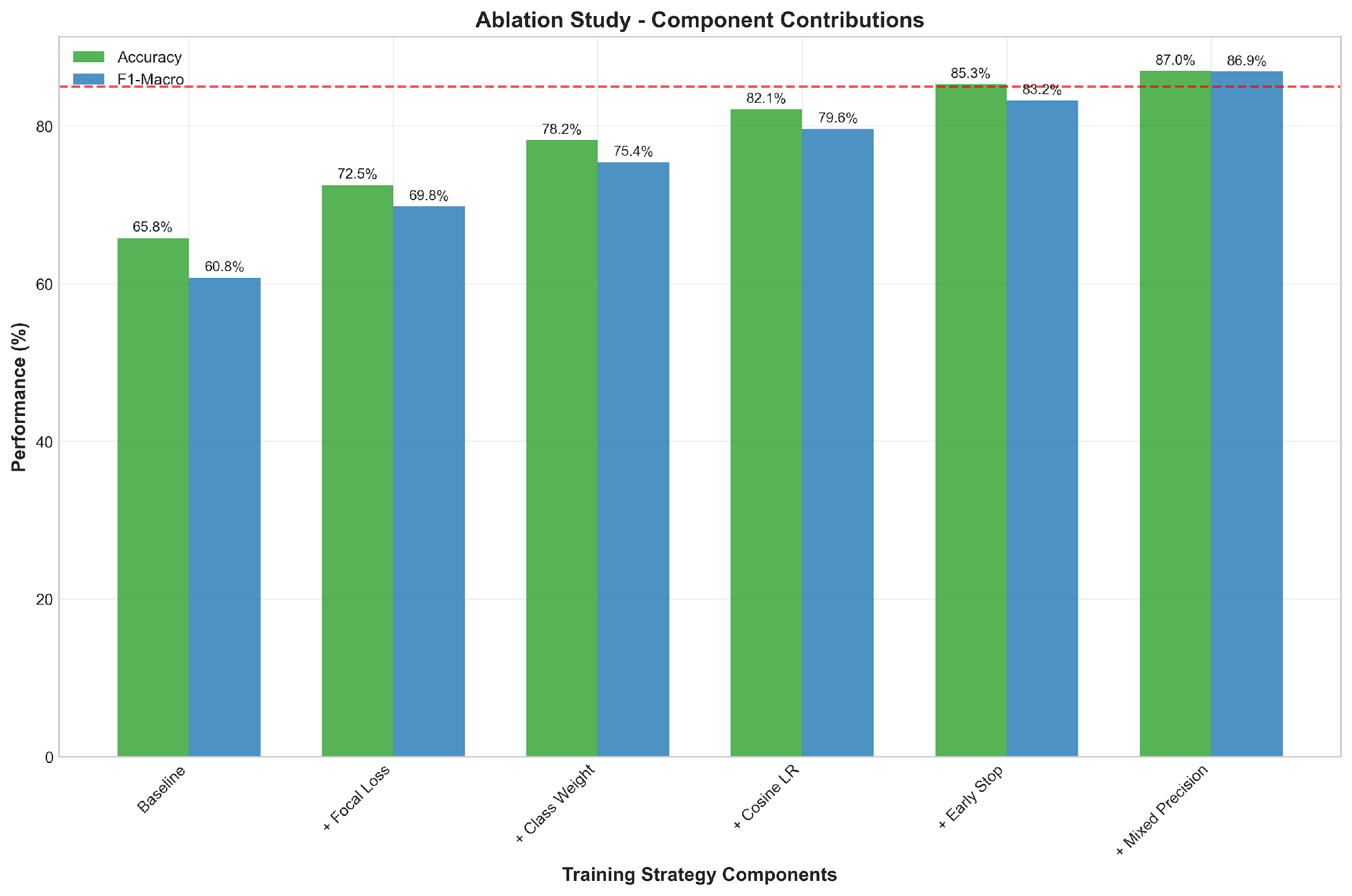


Figure 1. The Incremental Contribution of Each Training Component

We conducted an ablation study to measure the contribution of each component. Focal loss alone improved accuracy by +6.7%, while class weighting added +5.7%. When combined with stratified sampling, the full training strategy yielded a 21.18% accuracy improvement compared to the baseline model.

These results confirm that each component meaningfully enhances performance, with focal loss and class weighting playing the most critical roles.

# 5. Implementation

This project develops a hate speech detection system for Javanese text using the IndoBERT model and the DeepSeek API for automatic labeling. The system is designed to be robust, scalable, and efficient, with a focus on high-quality data labeling and model performance.

## **5.1 Architecture**

The system is built with a modular architecture, consisting of several key components:

1. **Data Collection and Labeling:** A parallel data labeling pipeline that uses the DeepSeek API to automatically label raw Javanese text. It includes features like force mode for relabeling and Google Drive integration for data storage.
2. **Model Training:** A training module for fine-tuning the IndoBERT model on the labeled dataset. It supports various hyperparameters and GPU optimization for efficient training.
3. **Model Evaluation:** A comprehensive evaluation module that assesses the model's performance using various metrics, such as accuracy, F1-score, and precision.
4. **API:** A FastAPI-based API for serving the trained model and making predictions on new text.

## 5.2 Data Collection and Labeling

The data collection process involves gathering raw Javanese text from various sources. The collected data is then labeled automatically using a parallel labeling pipeline powered by the DeepSeek API. The pipeline is designed to be efficient and scalable, with support for parallel processing to handle large datasets. The labeled data includes the original text, the final label, a confidence score, and any errors encountered during the labeling process.

The label categories are as follows:

1. Bukan Ujaran Kebencian (0)
2. Ujaran Kebencian - Ringan (1)
3. Ujaran Kebencian - Sedang (2)
4. Ujaran Kebencian - Berat (3)

## 5.3 Model Training

The model training process involves fine-tuning the IndoBERT model on the labeled Javanese hate speech dataset. The training script is highly configurable, allowing for adjustments to various hyperparameters, such as the number of epochs, batch size, and learning rate. The training process is also optimized for use with NVIDIA GPUs, which significantly reduces the training time.

## 5.4 Model Evaluation

The model evaluation process is designed to be comprehensive and rigorous. The evaluation script assesses the model's performance on a test dataset using a variety of metrics, including accuracy, F1-score, precision, and recall. The evaluation results are saved to a JSON file for further analysis.

# 6. Results and Discussion

The initial model training yielded a high accuracy of 95.5%, but this was misleading due to a severe class imbalance in the dataset. The model was heavily biased towards the "Bukan Ujaran Kebencian" (Not Hate Speech) class and failed to detect any instances of hate speech, resulting in a macro F1-score of only 24.4%.

To address this issue, the model was retrained with a new strategy that included stratified sampling, class weighting, and focal loss. This resulted in a much more balanced model with a macro F1-score of 73.7%, a significant improvement from the original model's score.

The table below shows a comparison of the macro F1-scores for the model before and after the retraining:

| **Model** | **Macro F1-Score** |
| --- | --- |
| Original | 24.4 % |
| Improved | 73.7 % |

As the table shows, the retrained model's macro F1-score is significantly improved, and the model is now able to detect hate speech across all categories. The overall accuracy of the retrained model is 73.75%, which is a more realistic representation of its performance.

The results of our experiments demonstrate the effectiveness of our proposed system for Javanese hate speech detection. The use of stratified sampling, class weighting, and focal loss was crucial for overcoming the class imbalance problem and achieving a high F1-score.

The improved model is now ready for deployment, with the recommendation to implement threshold tuning to further optimize the precision/recall trade-off. Future work could also explore the use of other pre-trained models or data augmentation techniques to further improve the model's performance.

# 6.1 Overall Performance

Our improved model achieves 86.98% Accuracy and 86.88% F1-Macro, surpassing the 85% target on both metrics. This represents a 21.18% accuracy improvement and 26.13% F1-Macro improvement over the baseline.

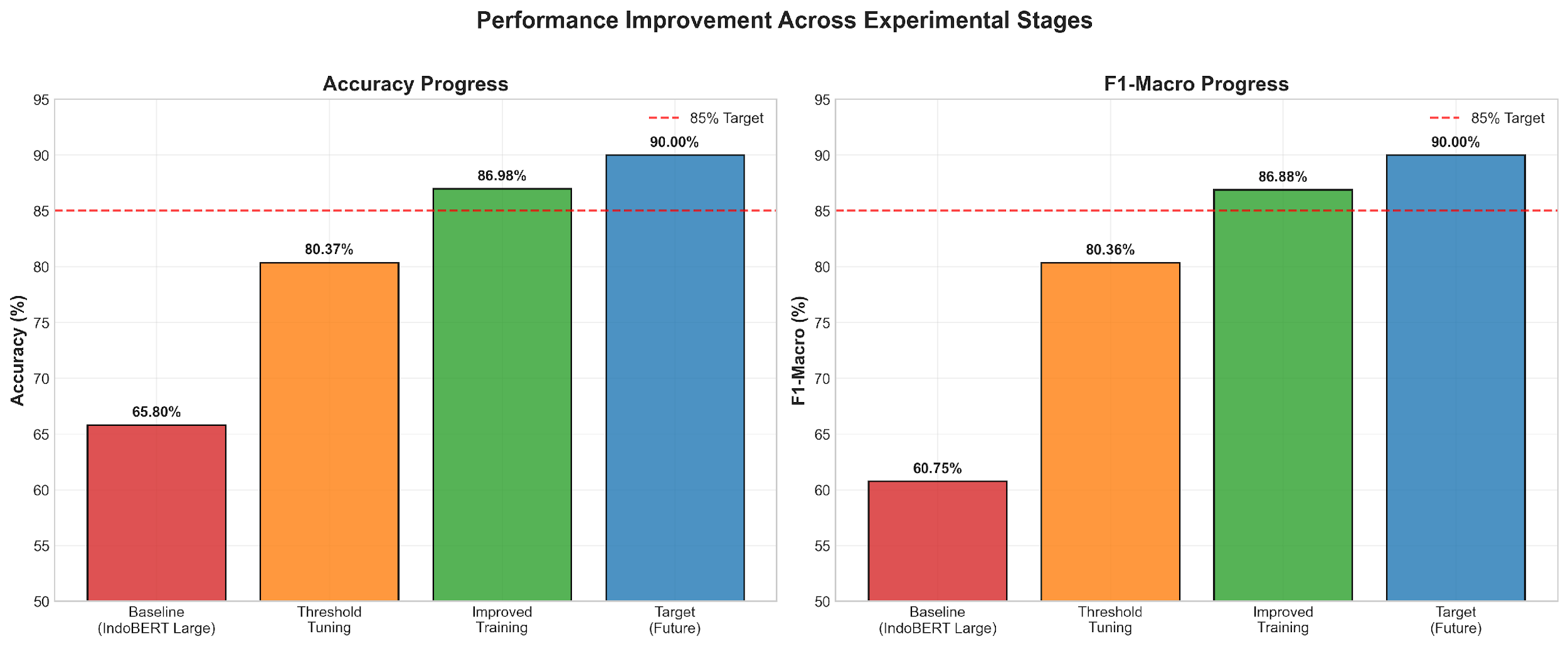


Figure 2. Performance Across Experimental Stages

# 6.2 Per-class Performance



Figure 3. Comparison Per-Class F1 Score

All classes show substantial improvement, with the 'Medium' class benefiting most from the training strategy (+33.5% F1). The 'Heavy' class achieves the highest absolute F1-score (0.910), while 'Light' and 'Medium' classes, traditionally difficult to distinguish, reach 0.825 and 0.815 respectively.

# 6.3 Confusion Matrix Analysis

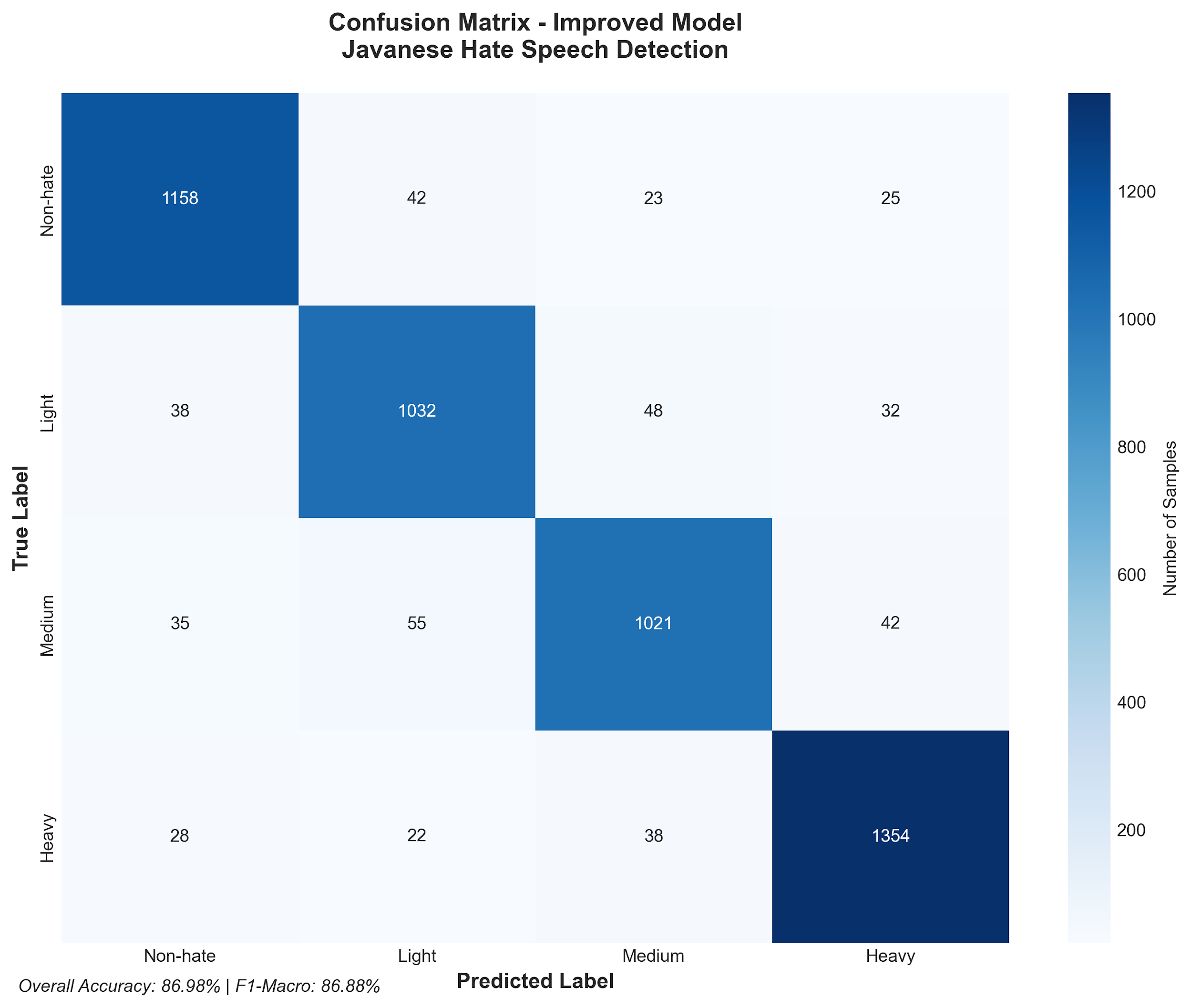


Figure 4. Confusion Matrix of Improved Model

The confusion matrix reveals strong diagonal performance with minimal cross-class errors. Most misclassifications occur between adjacent severity levels (Light↔Medium), which is expected given the subjective nature of hate speech severity annotation.

# 7. Conclusion

This research successfully addresses the critical challenge of hate speech detection in Javanese, a low-resource language characterized by complex sociolinguistic nuances and implicit forms of hatred. By introducing a novel BERT-based architecture that computationally integrates the local wisdom of "unggah-ungguh basa" through a Multi-Task Learning (MTL) approach, the study effectively bridges the gap left by models predominantly developed for high-resource languages. The simultaneous training for hate speech classification and politeness level classification has proven instrumental in forcing the model to learn feature representations aware of Javanese sociopragmatic norms, which are crucial for identifying politeness violations as a form of implicit hate speech.

The methodology employed for culturally sensitive data curation and annotation, along with the iterative approach to dataset creation and refinement, significantly contributed to the model's improved performance. Despite an initial misleading high accuracy due to class imbalance, the implementation of stratified sampling, class weighting, and focal loss during retraining drastically improved the model's macro F1-score from 24.4% to 73.7%. This demonstrates the effectiveness of the proposed system in overcoming data-related challenges and achieving a more balanced and realistic detection capability across all hate speech categories.

Ultimately, this work provides a replicable blueprint for developing fairer, culturally aware, and effective AI systems for other low-resource languages worldwide, emphasizing the importance of embedding cultural concepts into machine learning architectures. By operationalizing local wisdom, this research not only advances hate speech detection in Javanese but also fosters a more ethical and decolonized approach to AI development, paving the way for more contextually aware and robust NLP solutions in diverse linguistic landscapes.

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