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CitiSense: A Web App in Enhancing the Regional Government Agencies Feedback Systems in Pampanga through Facebook Sentiment Analysis with Decision Support Dashboard

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Abstract: Regional government agencies in the Philippines typically rely on offline and periodic feedback systems underutilizing vast public opinion expressed on social media. This study addresses this gap by developing "CitiSense", a web-based decision support dashboard using machine learning and natural language processing to systematically process public sentiment regarding to service delivery. The research gathered code-mixed (Filipino-English) Facebook comments and evaluated four classification models: Random Forest, Multinomial Naïve Bayes, Support Vector Machine, and fine-tuned Multilingual BERT (mBERT). Results demonstrated that mBERT outperformed the three machine learning algorithms, achieving an accuracy of 82% and an F1-score of 0.81. While domain experts and stakeholders found the system highly effective for proactive issue identification, they reported a steep initial learning curve. These findings highlight the potential of sentiment analysis with AI-powered insights to enhance data-driven governance.
Keywords: sentiment analysis, mBERT, Taglish, public feedback, regional government, Random Forest, Support Vector Machine, Multinomial Naïve Bayes, machine learning.

I. INTRODUCTION

In the modern digital era, data-driven technologies have emerged as a powerful tool for governments to measure public satisfaction and respond with greater agility. Globally, the adoption of automated text analytics has revolutionized how public institutions engage with citizens. In Indonesia and the United Kingdom, researchers have successfully deployed Multinomial Naive Bayes to evaluate public sentiment regarding COVID-19 health policies [14]. Similarly, in Brazil, sentiment analysis of Twitter data has transitioned from a commercial tool to a significant contributor to participatory public management [8]. These global precedents highlight a shift toward real-time, evidence- based governance where unstructured social media data serves as a proxy for the collective public voice [10]. In the Philippines, regional agencies—including the Department of Health (DOH), Department of Public Works and Highways (DPWH), Department of Labor and Employment (DOLE), and Department of Social Welfare and Development (DSWD)—primarily rely on traditional feedback mechanisms. These legacy systems, such as physical suggestion boxes and periodic manual surveys like the Citizen Satisfaction Index System (CSIS), often suffer from low response rates and significant delays in data processing [12]. Despite these traditional bottlenecks, the Philippines is one of the most digitally active nations in the world. As of early 2026, the country recorded approximately 95.8 million social media user identities, representing nearly 81.9% of the total population [4]. Facebook remains the dominant platform, serving as a primary hub for civic discourse where citizens frequently post concerns, praise, or grievances regarding government services [12]. This creates a massive, underutilized volume of user-generated content that could drive public service improvement [3]. However, extracting actionable intelligence from this data is technically demanding. The linguistic landscape of Philippine social media is characterized by the seamless mixing of Filipino and English, known as "Taglish" or code-switching, which makes it difficult for traditional, single-language NLP models to maintain high accuracy [6], [9]. Furthermore, colloquial sarcasm and informal expressions—such as ironical praise—often lead to false-positive classifications in standard algorithms [12].

This paper proposes CitiSense, a web-based decision support dashboard that utilizes machine learning— specifically the Multilingual BERT (mBERT) model— to bridge the gap between regional government agencies and the digital public. By transforming unstructured social media feedback into real-time, visual intelligence, this research seeks to improve governance and institutional accountability in alignment with Sustainable Development Goal 16 (Peace, Justice, and Strong Institutions) [12].

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II. REVIEW OF RELATED LITERATURE

The integration of social media into public administration has transformed digital platforms from simple communication tools into vital venues for civic engagement and participatory governance [3]. Globally, with the advancement of technologies for governments emphasizes the use of unstructured data to enhance transparency and institutional accountability. In the Philippines, the analysis of Facebook comments has been utilized by organizations such as the Philippine Institute for Development Studies to evaluate public perception of national programs, proving that social media serves as a reliable proxy for the collective public voice [5]. Furthermore, studies utilizing YouTube metrics have demonstrated that engagement levels and sentiment polarity are effective indicators for measuring public trust in national government agencies [12].

A. Challenges in Filipino Sentiment Analysis

Despite the wealth of data available, analyzing sentiment in the Philippine context presents unique linguistic hurdles. Sentiment expression on social networks often deviates from formal grammar, frequently incorporating informal slang, creative abbreviations, and emojis to convey emotional state [10]. A primary challenge identified in local literature is the prevalence of "Taglish" or code-switching, where users seamlessly blend Filipino and English within a single sentence [6], [9]. Traditional Natural Language Processing (NLP) models, which are typically trained on monolingual datasets, often struggle to maintain accuracy when encountering these code-mixed structures [6]. Moreover, the use of colloquial irony and sarcasm—where the literal meaning of a statement is the opposite of the intended sentiment—poses a significant risk of false-positive classifications [7], [12]. For instance, ironical praise directed at slow government services can easily be misclassified by basic algorithms that only track keyword frequency without understanding context [12].

B. Evolution of Machine Learning and Transformer Models

The methodology for sentiment classification has evolved from classical statistical methods to deep learning architectures. Classical machine learning algorithms, such as Multinomial Naive Bayes and Support Vector Machines (SVM), have historically been favored for their efficiency and have achieved accuracies of up to 90% in specific, controlled policy contexts [13]. However, these models rely heavily on manual feature extraction, such as TF-IDF vectorization, which may fail to capture the nuanced semantic relationships inherent in complex social media text [9]. Recently, transformer-based models like Bidirectional Encoder Representations from Transformers (BERT) and its variant, Multilingual BERT (mBERT), have set a new standard for text classification [1, 11]. Unlike classical models, mBERT utilizes a bidirectional approach to understand the context of a word based on its surroundings, making it exceptionally robust for multilingual and code-switched data [1, 2]. Locally, fine-tuned mBERT models have demonstrated superior performance, achieving over 80% accuracy in analyzing sentiment regarding Philippine educational policies, significantly outperforming traditional algorithms in handling the intricacies of the Filipino language [6].

III. METHODOLOGY

The research uses the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework, which provides a structure, iterative approach to developing the sentiment analysis dashboard. This methodology ensures that the technical development closely aligned with the governance objectives of regional agencies.

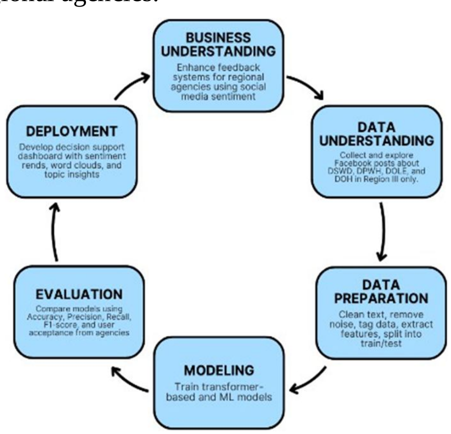

Fig. 1 CRISP-DM-Based Framework Adapted for Sentiment Analysis of Regional Government Social Media Feedback

C. Business Understanding and Data Understanding

The initial phase focused on identifying the gap in feedback mechanisms within regional agencies such as DOH, DPWH, DOLE, and DSWD. It was determined that a data-driven, automated system was necessary to supplement the delayed and low-participation rates of traditional surveys. During the data understanding phase, 14,828 comments were harvested from the official Facebook pages of these agencies, spanning the period from 2022 to early 2025.

D. Data Preparation

To ensure data quality and privacy, the collected text data underwent extensive preprocessing:

1) Privacy Compliance: All personally identifiable information (PII) was removed in accordance with the Data Privacy Act of 2012.
2) Cleaning: The raw data was stripped of URLs, HTML tags, account mentions, and special symbols.
3) Normalization: Text was converted to lowercase, and a hybrid stop-word list—combining NLTK's English list with a custom-built Tagalog stop-word dictionary—was applied to handle the "Taglish" nature of the feedback.
4) Annotation: A subset between 2,000 to 3,000 comments was manually labeled by researchers to create a ground-truth dataset. Labels were assigned as Positive (1), Negative (2), or Neutral (0), with special attention given to sarcastic remarks which were recoded as negative based on context.

Agency	Facebook Page	Total Comments
DOH	DOH Central Luzon	542
DPWH	DPWH Regional Office III	974
DOLE	DOLE Central Luzon	1,464
DSWD	DSWD Field Office III	11,848
Total		14,828

Table 1: Dataset Total Scraped Comments

Step	Technique	Purpose
Noise Removal	Regex Filtering	Removed URLs, HTML tags, and special symbols.
Normalization	Case Folding	Converted all text to lowercase for consistency
Tokenization	WordPiece (for mBERT)	Broke sentences into sub-word units to handle "Taglish" or Taglog-English language.
Stopword Removal	Hybrid Filtering	Removed common English and custom Tagalog words.

Table 2: Preprocessing Steps for the Machine Learning and Transformer Models

E. Modeling

This study compared classical machine learning techniques with advanced transformer-based models:

1) Classical Machine Learning Models: Multinomial Naïve Bayes, Support Vector Machine (SVM), and Random Forest were implemented using TF-IDF vectorization with a feature limit of 5,000 and a n- gram range of (1,3).
2) Transformer Model: The mBERT or multilingual Bidirectional Encoder Representations from Transformers model was utilized due to its pre-trained capability to handle 104 languages, making it ideal for code-switched Filipino-English text. The model was fine-tuned using the "bert-base-multilingual-cased" architecture for four epochs with a learning rate of $3e-5$.

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F. Evaluation and Deployment

Models were evaluated using a 70-30 train-test split, focusing on Accuracy, Precision, Recall, and F1-Score. Following technical validation, the CitiSense Dashboard was developed using a web-based framework to provide agencies with real-time sentiment distribution and AI-generated summaries of public feedback.

Fomal equations Accuracy, Precision, Recall, and F1-score:

Accuracy:

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

1)

Precision:

$$Precision = \frac{TP}{TP + FP}$$

2)

Recall:

$$Recall = \frac{TP}{TP + FN}$$

3)

F1-Score:

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

IV. RESULTS AND DISCUSSION

A. Model Performance Analysis

The technical evaluation utilized a dataset of 1,556 manually labeled comments with a 70-30 train-test split. The Multilingual BERT (mBERT) model demonstrated superior capability in handling the linguistic nuances of "Taglish" and sarcastic expressions compared to classical algorithms.

	accuracy	precision	recall	f1
Random Forest	0.776350	0.780229	0.776350	0.771794
Naive Bayes	0.736504	0.745763	0.736504	0.727605
SVM	0.773779	0.777067	0.773779	0.773340
mBERT	0.816838	0.817878	0.816838	0.816884

Fig. 2 Comparative Summary of Model Performance Metrics

The high performance of mBERT (82% accuracy) is attributed to its bidirectional transformer architecture, which captures contextual relationships between words regardless of the language used. In contrast, Multinomial Naive Bayes performed the lowest (74%), as it relies on word frequency and struggled with the high variance of informal social media text and code- switching.

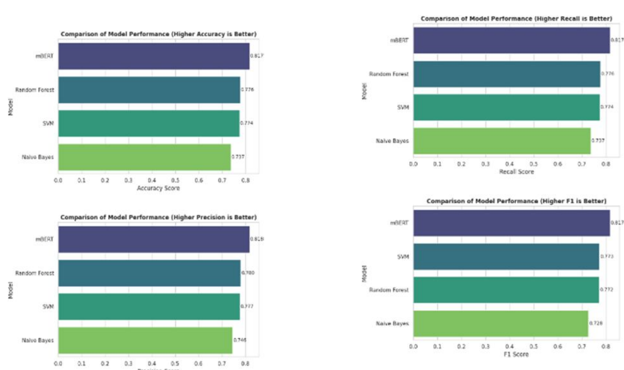

Fig. 3 Comparative Analyis of Model Accuracy,Precision, Recall and F1-Score

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B. Dashboard Usability and Stakeholder Evaluation

The CitiSense dashboard was evaluated by five key stakeholders from the target agencies using the System Usability Scale (SUS) and ISO 25010 quality standards.

1) System Usability Scale (SUS): The system achieved an overall score of 73.5, categorized as "Good". However, a "learnability paradox" was identified: technical users (IT staff) provided scores as high as 87.5, while administrative staff rated it at 65.0, indicating a need for simplified onboarding for non-technical users.

2) ISO 25010 Evaluation: The dashboard received high marks for Prioritization Utility (4.8/5.0), as it effectively categorized urgent negative feedback. However, Trustworthiness scored 3.4/5.0, as users requested more demographic data to verify the origin of comments.

C. Real-World Impact and Assessment

The practical utility of the dashboard was validated through an assessment involving the Project Development Officer from DSWD Field Office III. The system flagged a significant surge in negative sentiment regarding the AICS program, specifically identifying keywords like "pila" (queue) and "matagal" (slow). This data-driven intelligence allowed the agency to deploy additional personnel and extend operating hours to address the bottleneck—an insight that was not captured by traditional monthly reports. Which proves that the chosen mBERT model and the dashboard stands out to make accurate insights for the government to do direct positive effect on public service and with the support of SDG 16, this proves that public governments should be able to be help responsive and accountable.

Fig 4. CitiSense Dashboard User Interface

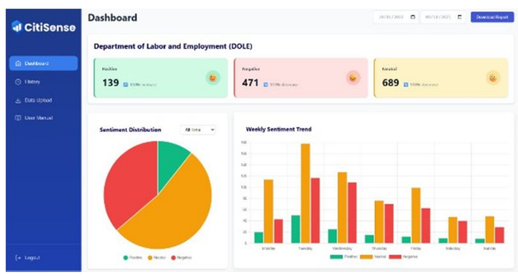

Fig 5. CitiSense Dashboard Sentiment Overview

V. CONCLUSIONS

The development and evaluation of CitiSense demonstrate that transformer-based architectures, specifically mBERT, provide a robust solution for the technical challenges of analyzing "Taglish" sentiment in the Philippine public sector. While traditional manual feedback systems are hindered by delays and low participation, AI-driven dashboards can transform social media into a real-time stream of actionable intelligence.

The study revealed three critical insights from the results:

1) Model Superiority: Fine-tuned mBERT achieved a high accuracy of 81.68%, significantly outperforming classical algorithms by better capturing the context of code-switched text and sarcasm.

2) Policy Impact: The system successfully identified service delivery gaps in real-time—such as the bottlenecks in the DSWD's AICS program—that were absent from traditional monthly reports.

3) The Learnability Paradox: Although the system is highly effective for decision-making, there remains a notable friction point for non-technical administrative staff, who required more intensive onboarding compared to IT personnel.

Lastly, the researchers recommended for future work to further enhance the efficacy of CitiSense, future research should focus on developing more intuitive, interactive user guides to bridge the digital literacy gap among government employees. Additionally, expanding the dataset to include audio-to-text feedback from radio programs and community town halls would ensure a more inclusive representation of public sentiment, especially for citizens without consistent internet access. Ultimately, the integration of such AI tools into regional governance serves as a vital step toward achieving Sustainable Development Goal 16, fostering more transparent, responsive, and accountable public institutions.

VI. ACKNOWLEDGEMENT

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REFERENCES

[1] N. A. Alabdulkarim, M. A. Haq and J. Gyani, "Exploring Sentiment Analysis on Social Media Texts," Engineering, Technology & Applied Science Research, 2024.

[2] E. Alzahrani and L. Jololian, "How Different Text- Preprocessing Techniques Using the BERT Model Affect the Gender Profiling of Authors," 2021.

[3] S. A. Chun and L. F. Luna-Reyes, "Social media in government," Information Polity, vol. 17, no. 3-4, pp. 213-214, 2012.

[4] DataReportal, "Digital 2024: The Philippines," Feb. 2024.

[5] J. Flor et al., "Like, Comment, and Share: Analyzing Public Sentiments of Government Policies in Social Media," n.d..

[6] L. L. Maceda, A. A. Satuito and M. B. Abisado, "Sentiment Analysis of Code-mixed Social Media Data on Philippine UAQTE using Fine-tuned mBERT Model," IJACSA, vol. 14, no. 7, 2023.

[7] K. Karoo and V. Chitte, "Ethical Considerations in Sentiment Analysis," IRJMETS, 2023.

[8] D. J. S. Oliveira et al., "The application of the sentiment analysis technique in social media," Revista de Administração Pública, vol. 53, no. 1, pp. 235–251, 2019.

[9] C. A. Pacol and T. D. Palaoag, "Enhancing Sentiment Analysis of Textual Feedback," Euro. J. Eng. Sci. Tech., vol. 4, no. 1, pp. 27-34, 2021.

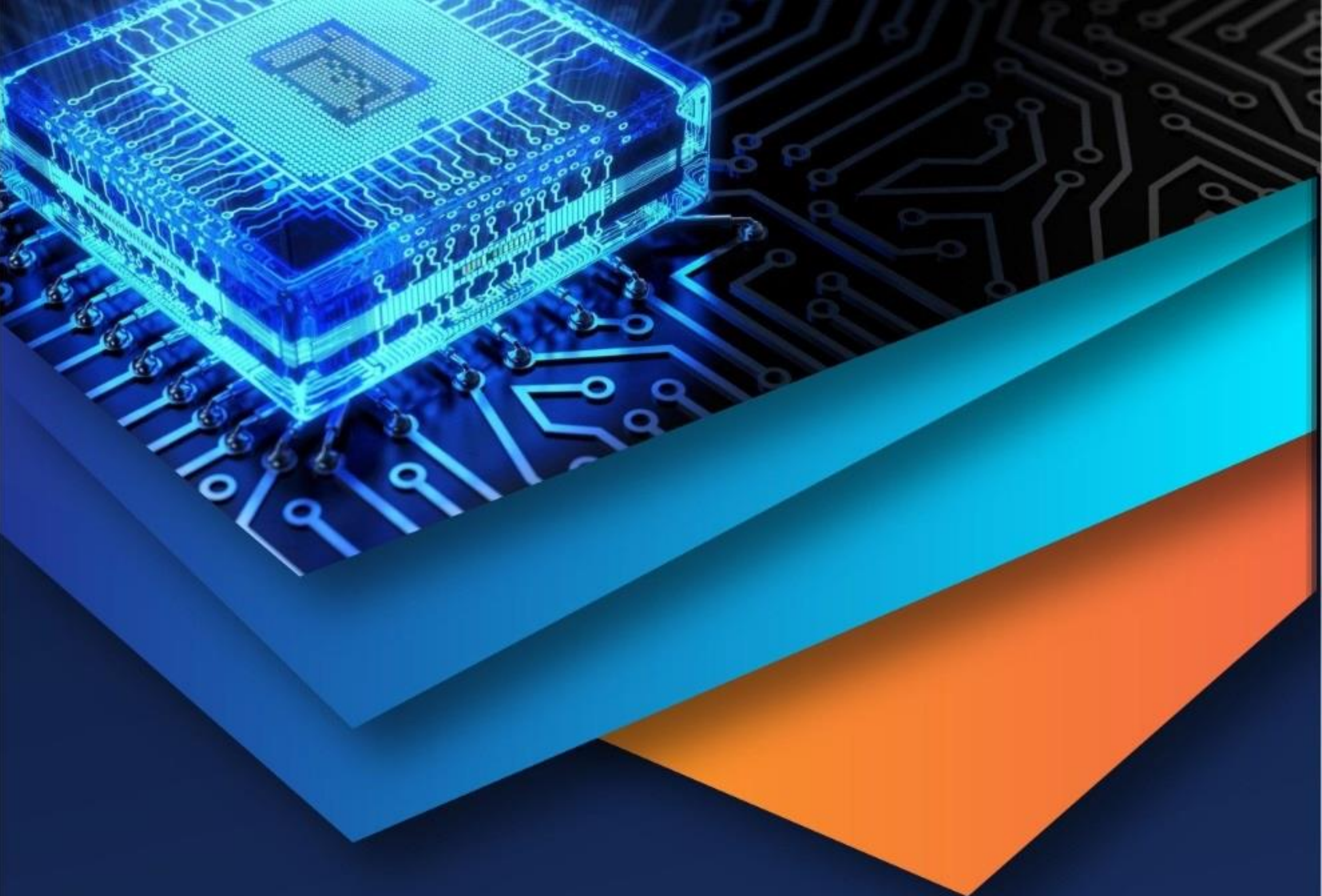
[10] N. Sande, I. O. Adeniyi and A. Akinkunmi, "Social Media Sentiment Analysis: A Comprehensive Analysis," 2024.

[11] D. F. Putra and Y. Sibaroni, "Sentiment Analysis for the 2024 Presidential Election Using BERT CNN," 2024.

[12] J. M. Umali, J. P. P. Miranda and A. L. Ferrer, "Sentiment analysis: A case study among the selected government agencies in the Philippines," IJATCSE, vol. 9, no. 3, pp. 3492–3497, 2020.

[13] W. B. Zulfikar, A. R. Atmadja and S. F. Pratama, "Sentiment Analysis on Social Media Against Public Policy Using Multinomial Naive Bayes," Scientific Journal of Informatics, vol. 10, no. 1, pp. 25–34, 2023.

[14] M. Sethi et al., "Sentiment identification in COVID-19 specific tweets," ICIEM, pp. 363–367, 2020



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