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AI-Based Multilingual Complaint Analysis and Emotion-Aware Priority Prediction System

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***Abstract*— *A web-based program called the Complaint Management System was created to effectively handle and examine consumer complaints. Users can file complaints online through the system, and Natural Language Processing (NLP) methods are used to process them. Complaints are categorized using a transformer-based paradigm into groups like delivery, payment, and service problems. In order to prioritize significant complaints, it also uses sentiment analysis and urgency prediction. The system creates automated reports in Excel formats and safely archives complaint data. An administrator dashboard aids in tracking the operation of the system as a whole and complaint trends. Better customer satisfaction results from this project's improved reaction time and decreased manual labor.*

***Keywords*—** NLP Techniques, Transformer Model-XML-RoBERTa, DistilRoBERTa.

I. Introduction

A branch of artificial intelligence called natural language processing (NLP) makes it possible for computers to comprehend and process human language. It blends methods from machine learning, linguistics, and computer science. NLP facilitates the analysis of vast volumes of text and the extraction of valuable information. Applications such as chatbots, text classification, and sentiment analysis make extensive use of it. For increased accuracy, contemporary NLP systems employ transformer models and deep learning. NLP is crucial for enhancing intelligent systems and automating language-based processes.

Natural Language Processing (NLP) is the primary application for the Transformer model, a sophisticated deep learning architecture. It was created to get around the drawbacks of the conventional RNN and LSTM models. To comprehend the relationships between words in a phrase, the transformer employs a technique known as self-attention. This improves the model's ability to represent long-distance dependencies. It is quicker and more effective than previous models since it processes data in parallel. Popular systems like BERT and GPT are based on transformer models. They are frequently employed for tasks including sentiment analysis, translation, and text classification.

The"cardiffnlp/twitter-xlm-roberta-base-sentiment" transformer model is used for sentiment analysis. This model is based on the multilingual transformer model XLM-RoBERTa architecture. It has been specially trained to analyze attitudes in textual data, such as social media comments and user reviews. Text is classified by the model into sentiment categories, including positive, negative, and neutral. It uses the self-attention process to correctly understand the meaning and context of words. Consequently, sentiment analysis of customer complaints is more precise. The process makes it easier to identify customer emotions and prioritize issues effectively.

To detect emotions, the transformer model "j-hartmann/emotion-english-distilroberta-base" is employed. The DistilRoBERTa architecture, a more compact and effective variant of the RoBERTa transformer model, serves as the foundation for this model. It has been specially taught to recognize a variety of emotions in English texts, including fear, rage, sadness, and happiness. To comprehend the context and meaning of words in a phrase, the model employs a self-attention process. This aids in precisely assessing the emotional content of client complaints. The technology can enhance complaint prioritization and response by identifying emotions and gaining a deeper understanding of consumer sentiment.

Consumers regularly use internet channels to voice their concerns and provide feedback. Handling these concerns by hand can be laborious, ineffective, and error-prone. The Complaint Management System, an intelligent web-based tool that automates the process of processing consumer complaints, was created in order to address this issue.

This approach makes the process easy and accessible by enabling consumers to file complaints via an online portal. To properly comprehend the text content, Natural Language Processing (NLP) techniques are used to analyze the filed complaints. To group complaints into categories including delivery, payment, and service difficulties, a transformer-based methodology is used. To detect key complaints and rank them appropriately, the system also uses sentiment analysis and urgency prediction.

For improved tracking and administration, the application offers automatic report production capabilities in addition to securely storing complaint records. System performance and complaint patterns can be tracked with an admin dashboard. All things considered, this project uses intelligent automation to increase productivity, decrease manual labor, and raise customer happiness.

II. Literature Review

Sentiment analysis and complaint prioritization have been widely studied in previous research. Deshmukh and Shiravale [1] proposed a priority-based sentiment analysis model to respond quickly to citizen complaints. However, their approach mainly focused on polarity detection and basic priority mapping, without deep contextual understanding using transformer-based models.

Early machine learning-based sentiment classification methods were introduced by Pang et al. [2] and contextual polarity detection by Wilson et al. [3]. These works relied on traditional machine learning and feature engineering techniques, which lack deep semantic representation compared to modern transformer architectures. Deep learning models such as recurrent neural networks were explored by Irsoy and Cardie [4], improving performance over traditional approaches. However, RNN-based systems struggle with long-range dependency understanding when compared to transformer-based self-attention mechanisms introduced by Vaswani et al. [12].

The introduction of BERT by Devlin et al. [8] and Toutanova et al. [7] significantly improved contextual text representation. Later works such as Reddy and Kumar [13] applied BERT for sentiment analysis in retail applications. However, most of these studies focus only on sentiment polarity and do not integrate emotion classification with automated priority assignment.

Emotion-based prioritization was studied by Umer et al. [16], but their work mainly targeted bug reports and was not designed for multilingual citizen complaint systems. Similarly, lexicon-based and aspect-based approaches proposed by Jurek et al. [10] and Saeidi et al. [11] rely on domain-specific datasets and do not generalize well to multilingual environments.

Recent surveys such as Xu et al. [6], Tortoni et al. [19], and Paul et al. [20] highlight the growing importance of transformer-based sentiment systems in real-world applications. However, most studies do not combine multilingual transformer models with lightweight deployment mechanisms for real-time complaint management.

III. Methodology

The proposed system analyzes user complaints using natural language processing and transformer-based models for priority prediction and emotion recognition. First, customer complaints are collected via a web-based interface and stored in a database. Preprocessing methods such as tokenization, cleaning, special character removal, and lowercasing are applied to the collected text data in order to improve text quality.

After preprocessing, the cleaned complaint text is given into a transformer model that has already been trained, called j-hartmann/emotion-english-distilroberta-base, to determine the underlying emotion that was expressed. The transformer model uses a self-attention mechanism to understand contextual meaning and accurately classify emotions such as fear, happiness, fury, sadness, and others.

Based on the identified emotion and sentiment intensity, the technology assigns a priority rating (High, Medium, or Low) to the complaint. Complaints expressing extremely negative emotions, like anger or impatience, are given precedence in order to ensure a speedier response. Finally, by viewing and saving the classified complaints along with their corresponding priority levels, the administrator may act swiftly and make choices.

IV. Proposed Architecture

The proposed architecture presents a multilingual, transformer-based complaint analysis and prioritization system. The workflow begins with user complaint text input in English, Tamil, or other supported languages. A language-agnostic preprocessing module performs text cleaning and tokenization to prepare the input for model processing. The preprocessed text is passed to the XLM-RoBERTa encoder, which generates deep contextual embeddings using a self-attention mechanism. These embeddings capture semantic meaning across multiple languages.

The extracted features are fed into a fine-tuned emotion classification module to predict emotional states such as anger, sadness, fear, and happiness. Based on the predicted emotion and sentiment intensity, a priority assignment module categorizes complaints into High, Medium, or Low levels. Finally, the complaint is routed to the management queue for administrative action. This architecture ensures accurate multilingual understanding, automated prioritization, and efficient complaint handling.

Finally, the analyzed complaint, along with its predicted emotion, category, and priority level, is stored in the database and displayed on the admin dashboard for monitoring and decision-making. This architecture ensures automation, accuracy, and faster complaint management.

As shown in Fig. 4, the proposed architecture integrates XLM-RoBERTa and DistilRoBERTa for multilingual emotion classification.

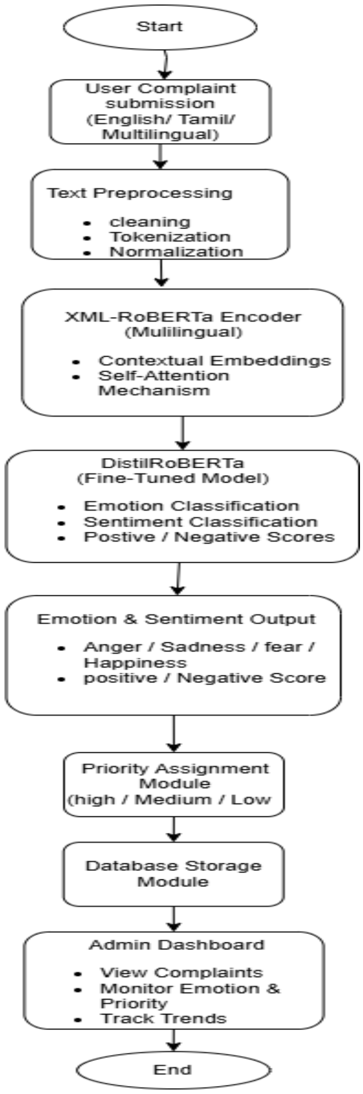

Fig.1 Proposed System Architecture of Multilingual Transformer-Based Complaint Analysis and Management System

A. XML-RoBERTa MODEL

Complaint analysis and emotion recognition are two applications of the XLM-RoBERTa model. Facebook AI created XLM-RoBERTa, a multilingual transformer-based model, based on Ashish Vaswani et al.'s Transformer architecture. It is quite good at handling both English and non-English inputs because it was trained on a sizable multilingual dataset that included text in several languages.

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To comprehend the contextual relationships between words in a sentence, the model employs a self-attention mechanism. In contrast to conventional machine learning models, XLM-RoBERTa enhances classification accuracy while capturing deep semantic meaning. The model used in this study has been tweaked for emotion recognition, allowing the system to categorize complaints into various emotional groups, including fear, happiness, sorrow, and rage.

The multilingual capabilities of XLM-RoBERTa enhances generalization and prediction performance because the dataset includes English text as well as Tamil or other language inputs that the system must process. A priority level (High, Medium, or Low) is subsequently assigned based on the identified emotion, thereby automating the handling of complaints..The multilingual complaint processing architecture of the proposed system is illustrated in Figure 2.

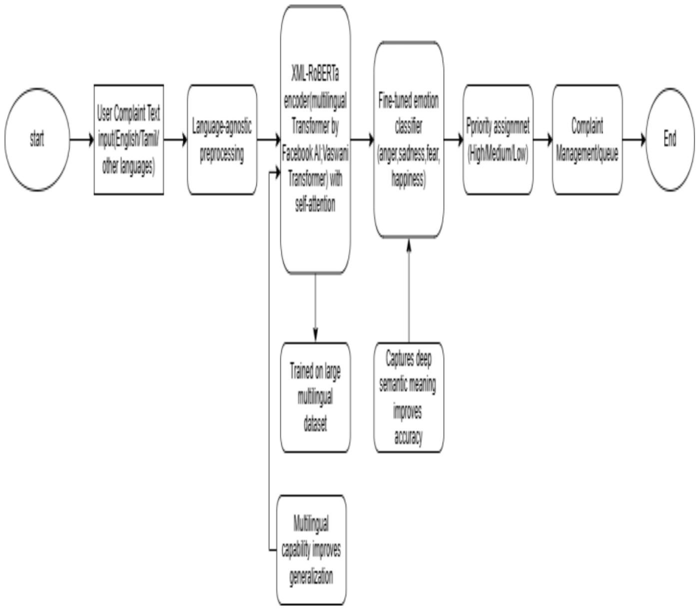

Fig. 2 Multilingual XLM-RoBERTa-Based Complaint Processing and Priority Assignment Framework

1. User complaint text input (English/Tamil/other languages):

Multiple languages, including Tamil, English, and other regional languages, can be used to enter user complaints into the system. This multilingual feature guarantees that users can freely file complaints in the language of their choice. A transformer-based model is then used to process and analyze the incoming text in order to identify emotions and anticipate priorities.

2. Language-agnostic preprocessing

Regardless of the input language, language-agnostic preprocessing is used to clean and standardize complaint content. The procedure involves keeping important words while eliminating excessive spaces, special letters, and superfluous symbols. Before sending the text to the transformer model for analysis, this guarantees that the system can manage multilingual inputs efficiently.

3. XLM-RoBERTa encoder with self-attention

An effective transformer-based model for processing multilingual text is the XLM-RoBERTa encoder. It records the contextual associations between words in a sentence via a self-attention mechanism. This makes it possible for the model to precisely comprehend semantic meaning for the purposes of emotion detection and complaint analysis.

4. Fine-tuned emotion classifier

The system recognizes emotions like fear, happiness, sadness, and rage from complaint text using a refined emotion categorization model. To increase prediction accuracy, emotion-labeled data is used to further train the transformer model that has already been trained. This makes it possible for the system to efficiently identify the emotional tone of complaints in order to assign them a priority.

5. Priority assignment

A priority level, such as High, Medium, or Low, is assigned by the system based on the sentiment intensity and detected emotion. High priority complaints are those that convey intensely unpleasant feelings like rage or dissatisfaction. Faster response times and effective complaint handling are made possible by this priority assignment system.

6. Complaint management / queue

The complaint management module uses an organized queuing system to arrange complaints according to their given priority levels. To guarantee prompt consideration, high-priority complaints are positioned at the head of the line. When it comes to addressing consumer concerns, this

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methodical queue management increases response time and overall effectiveness.

7. Trained on large multilingual dataset

A sizable multilingual dataset with text in several languages is used to train the model. It can comprehend verbal patterns, contextual meaning, and emotional expressions in a variety of languages because to its intensive training. Consequently, the system is able to precisely evaluate complaints that are submitted in a variety of language formats.

8. Captures deep semantic meaning improves accuracy

By comprehending the contextual relationships between words in a phrase, the model is able to capture deep semantic meaning. It examines the entire sentence structure and intent, in contrast to conventional keyword-based approaches. The classification of emotions and overall prediction accuracy are greatly enhanced by this deeper comprehension.

9. Multilingual capability improves generalization

The model can efficiently process text from several languages thanks to its multilingual capacity. This improves the model's capacity to generalize across a variety of language inputs. Because of this, the system continues to operate consistently even when dealing with multilingual complaint data.

B. Distilroberta model

The DistilRoBERTa model is used to classify customer complaints based on sentiment and identify emotions. Using knowledge distillation techniques, DistilRoBERTa is a speedier and lighter version of RoBERTa. It uses less memory and computational complexity while maintaining the majority of the performance of large transformer models. Ashish Vaswani et al.'s Transformer architecture, which makes use of self-attention mechanisms to comprehend contextual links in text, serves as the model's foundation.

Compared to conventional machine learning techniques, DistilRoBERTa enhances classification accuracy and efficiently extracts deep semantic content from complaint statements. The model is adjusted in this approach to categorize emotions including irritation, grief, and rage. To guarantee a quicker reaction to serious concerns, the system determines a priority level (High, Medium, or Low) based on the anticipated emotion. DistilRoBERTa is appropriate for real-time complaint analysis systems due to its smaller size and quicker processing speed. The detailed workflow of the proposed complaint analysis and prioritization system is presented in Figure 3.

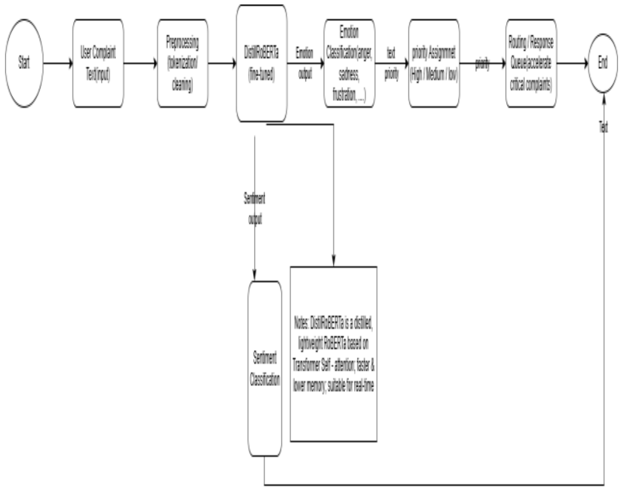

Fig.3 Workflow of Complaint Classification, Priority Assignment, and Routing Mechanism

1. User Complaint Text

The main input into the system is the User Complaint Text. Via the application interface, users can voice their grievances in normal language. After that, this input text is parsed and examined to determine priority and identify emotions.

2. Preprocessing (tokenization/cleaning)

The complaint text is cleaned and tokenized during preprocessing in order to get it ready for model analysis. The text is separated into meaningful tokens and superfluous letters, excess spaces, and noise are eliminated. This stage guarantees that the incoming data is organized and appropriate for precise priority prediction and emotion classification.

3. DistilRoBERTa (fine-tuned)

Emotion-labeled data is used to refine the DistilRoBERTa model, which enhances classification performance for complaint analysis. The pre-trained transformer is adjusted

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to the particular task of emotion recognition by fine-tuning. This maintains quicker processing and lower computing costs while improving forecast accuracy.

4. Emotion Classification

The underlying emotional tone of the complaint language, such as anger, grief, frustration, and happiness, is identified using the emotion categorization module. The refined transformer model predicts the dominant emotion with accuracy by examining contextual meaning. Each complaint's proper priority level is then established using this emotional understanding.

5. Priority Assignment

Based on the identified emotion and its strength, the priority assignment module assigns complaints to one of three levels: High, Medium, or Low. Strongly unfavorable complaints are given top priority and require prompt action. Critical concerns are handled effectively and resolved more quickly because to this organized priority.

6. Routing / Response Queue (accelerate critical complaints)

Based on their designated priority level, the routing and response queue module routes complaints to the relevant department. To speed up resolution, high-priority complaints are automatically placed to the front of the line. This system guarantees prompt action and effective management of urgent problems.

7. Sentiment Classification

The general polarity of the complaint text—whether positive, negative, or neutral—is examined by the sentiment categorization module. It assesses words' contextual meaning to ascertain the message's emotional tone. This data enhances the precision of priority assignment and aids in emotion recognition.

V. Feature Extraction

In order to convert unprocessed complaint text into useful numerical representations that the classification models can use, the feature extraction step is essential. In order to extract deep contextual data from customer complaints, this project uses two sophisticated Transformer-based models, XLM-RoBERTa and DistilRoBERTa.

A sizable multilingual corpus was used to train the multilingual Transformer model XLM-RoBERTa. It can comprehend the semantic connections between a variety of languages, including Tamil, English, and other regional tongues. The approach captures contextual relationships between words in a phrase, regardless of their position, by utilizing the self-attention process. This makes it possible for the system to comprehend the complaint text's subtle connotations, sarcasm, emotional intensity, and implicit feelings.

Conversely, DistilRoBERTa is a computationally efficient and lightweight version of RoBERTa. It drastically reduces model size and inference time while maintaining the majority of the performance of bigger Transformer models. Because of this, it can be used with real-time complaint analysis systems. DistilRoBERTa produces contextual embeddings at a reduced computing cost while maintaining semantic and affective information.

Both models are used to tokenize and embed the complaint text during feature extraction. High-dimensional feature vectors that encapsulate contextual relationships, emotional cues, and semantic meaning are represented by the output embeddings. Following that, these feature vectors are transferred to downstream classification layers for priority assignment, sentiment classification, and emotion detection.

The suggested approach improves accuracy, generalization, and performance in complaint analysis by fusing the advantages of DistilRoBERTa (quick and efficient contextual encoding) and XLM-RoBERTa (deep semantic representation and multilingual comprehension). The overall architecture of the proposed complaint analysis system is illustrated in
Figure 4.

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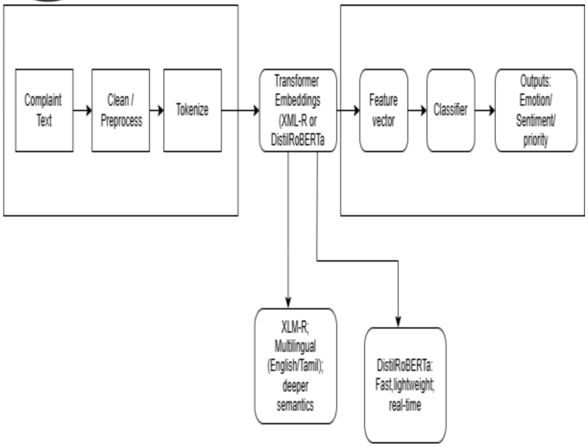

Fig .4 Proposed Transformer-Based Complaint Analysis Architecture

1. Complaint Text

This module represents the initial input stage of the system where users submit their complaints. The complaint can be written in English, Tamil, or other supported languages. The system is designed to handle multilingual inputs efficiently. This raw complaint text serves as the primary data for further processing and analysis.

2. Clean / Preprocess

In this stage, the input complaint text undergoes preprocessing to remove noise and unwanted characters. Special symbols, extra spaces, and irrelevant words are eliminated to improve text quality. Normalization techniques are applied to standardize the format of the text. This step ensures that the data becomes suitable for tokenization and model processing.

3. Tokenize

Tokenization is the process of breaking the cleaned text into smaller units called tokens. These tokens may represent words or sub-words depending on the transformer tokenizer. This step converts human-readable text into machine-understandable format. Proper tokenization improves contextual understanding during embedding generation.

4. Transformer Embeddings (XLM-R / DistilRoBERTa)

In this stage, transformer-based models generate contextual embeddings from the tokenized text. XLM-RoBERTa captures multilingual semantic meaning using self-attention mechanisms. DistilRoBERTa provides lightweight and faster processing for real-time classification. These embeddings represent the deep contextual features of the complaint text.

5. Feature Vector

The embeddings produced by the transformer model are converted into numerical feature vectors. These vectors capture semantic relationships and emotional intensity within the text. The feature vector acts as the input for the classification layer. It enables accurate emotion and sentiment prediction.

6. Classifier

The classifier layer processes the feature vector to categorize the complaint. It predicts emotion labels such as anger, sadness, fear, or happiness. It also determines the sentiment polarity (positive or negative). Based on prediction confidence, the system prepares results for priority assignment.

7. Outputs: Emotion / Sentiment / Priority

This module generates the final output of the system. The predicted emotion and sentiment scores are displayed to the user or admin. Based on emotional intensity, the complaint is assigned a priority level such as High, Medium, or Low. This helps in effective complaint management and decision-making.

8. XLM-R (Multilingual: English/Tamil; deep semantics)

XLM-RoBERTa is used to handle multilingual inputs effectively. It is trained on large multilingual datasets, enabling better generalization across languages. The model captures deep semantic relationships using self-attention mechanisms. This improves classification accuracy for both English and Tamil complaints.

9. DistilRoBERTa (Fast, Lightweight; Real-Time)

DistilRoBERTa is a compressed version of RoBERTa designed for faster inference. It reduces model size while maintaining high accuracy. This makes the system suitable for real-time complaint analysis. The lightweight nature ensures efficient deployment in web-based applications.

VI. Results And Discussions

The Complaint Management System's entry module is the Login Page. Through role-based authentication, it gives administrators and users several access possibilities. People can file and monitor complaints using the User Login. Authorized workers may effectively manage, monitor, and address concerns with the use of the admin login. Unauthorized use is avoided and system security is enhanced by this organized access control. While preserving safe login capabilities, the user experience is improved by the straightforward and easy-to-use UI. Figure5 shown as Login Interface of the Proposed Complaint Management System.

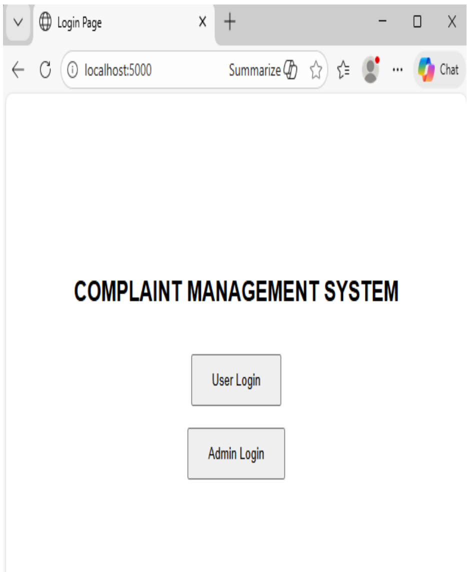

Fig.5 Login Interface of the complaint Management System

Figure 6 shows the proposed system's admin login page and user complaint page. Registered users can use a text input interface on the User Complaint Page to submit their complaints. With the help of this module, users can clearly define problems, which are subsequently analyzed for priority and emotion analysis. The straightforward layout guarantees accessibility and ease of filing complaints. Authorized administrators can authenticate securely using the Admin Login Page. The complaint management dashboard is only accessible with verified credentials. Sensitive complaint data cannot be accessed by unauthorized parties thanks to our role-based authentication method.

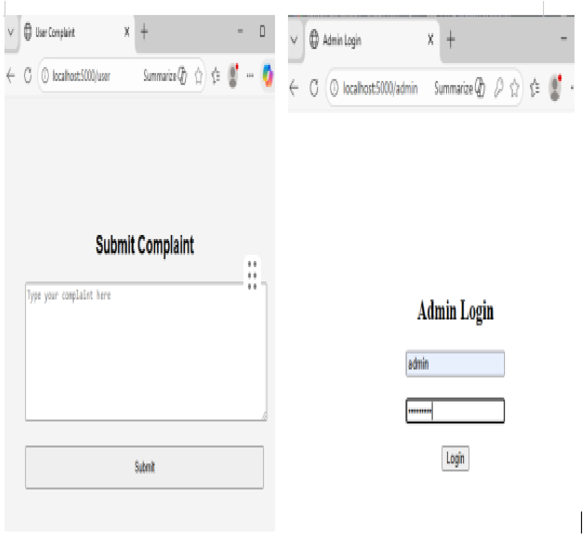

Fig. 6 User Complaint Submission Page and Admin Login Interface

Figure 7 shows the pages for the User Complaint Submission and Prediction Result. Through a structured input interface, users can enter their complaint text on the User Complaint Page. After being filed, the complaint is processed by the system, which analyzes it using the trained Transformer-based model. Sentiment, emotion, urgency level, and complaint type are among the classified outputs that are shown on the Prediction Result Page. This computerized analysis aids in effectively determining the issue's type and level of severity. Transparency is increased and efficient decision-making in complaint handling is supported by the organized result presentation.

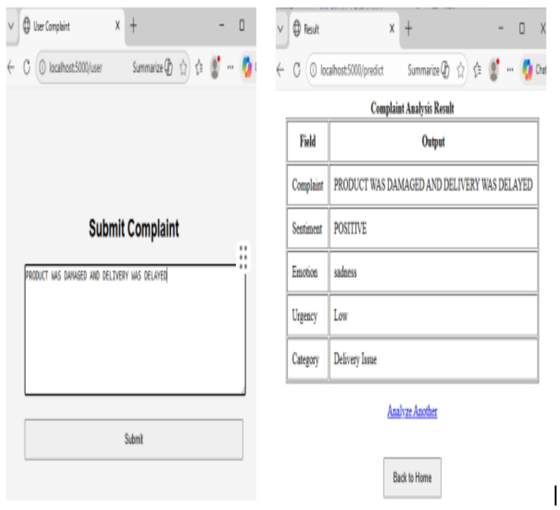

Fig. 7 User Complaint Submission Interface and Complaint Analysis Result page

Figure 8 displays the admin dashboard for the suggested complaint management system. A consolidated interface for tracking and handling all complaints is offered by this module. The dashboard shows the category, urgency level, anticipated sentiment, and emotion in addition to the complaint facts. Administrators are able to rapidly examine complaint trends and pinpoint important problems thanks to this organized tabular format. The system prioritizes complaints according to their level of urgency, which facilitates effective decision-making. In order to improve management and reaction planning, administrators can also access summary complaint analytics through the report generating feature.

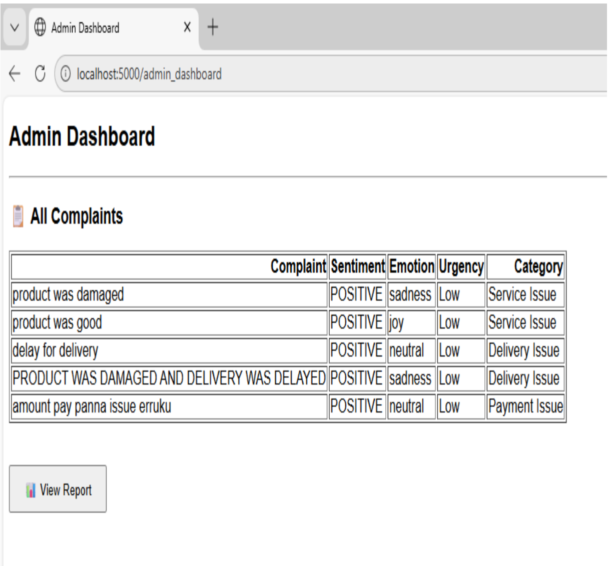

Fig. 8 Admin Dashboard Displaying Complaint Analysis and Classification Results

As seen in Figure 9, the Admin Dashboard has a report production feature. The system automatically creates and downloads an Excel file with all complaint records when the administrator chooses the "View Report" option. The complaint content, anticipated sentiment, emotion, degree of urgency, and category classification are all included in the exported report. This feature makes it easier to store structured data and analyze complaint trends offline. Transparency is increased and managerial decision-making is supported by the Excel-based reporting system. Additionally, it enables administrators to keep written records for future use and performance reviews.

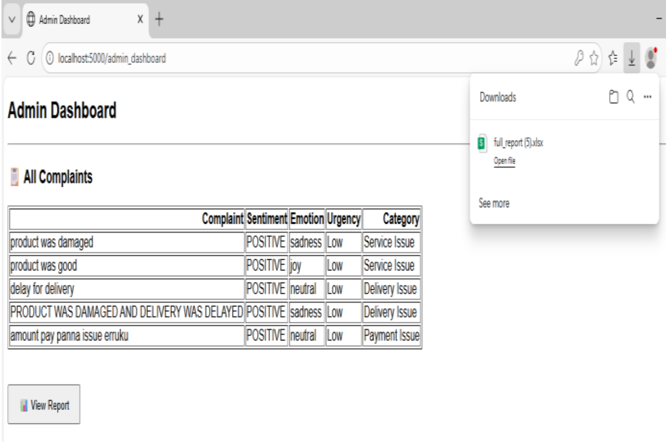

Fig. 9 Admin Dashboard with Automated Excel Report Generation

The model performance improved across iterations, with higher confidence scores observed in the final fine-tuned model. Positive terms such as "excellent" (0.93) and "satisfied" (0.90) received strong positive polarity scores, while negative expressions like "frustrated" (-0.91) and "damaged" (-0.89) showed high negative confidence. This indicates that the optimized transformer model effectively captures sentiment intensity and contextual meaning.as show Table 1 below related to terms and scores.

Iteration	**Positive Terms (Score)**	**Negative Terms (Scores)**
Iteration 1	Good(0.72), Satisfied(0.75)	Delay (-0.70), Issue(-0.68)
Iteration 2	Happy(0.84), Excellent(0.88)	Damaged (-0.82), Poor(-0.85)
Iteration 3	Satisfied(0.90), First delivery (0.86), Excellent(0.93)	Frustrated (-0.91), Damaged (-0.89), Delay(-0.87)

Table 1 Model Iteration and Sentiment Terms Analysis

VII. CONCLUSION

An intelligent multilingual complaint management system built on transformer-based deep learning models is presented in this work. Effective sentiment analysis, emotion identification, and priority classification of user complaints are achieved by integrating XLM-RoBERTa and DistilRoBERTa in the suggested framework. The system processes complaints in many languages, including Tamil and English, with accuracy by utilizing cross-lingual representation learning and contextual embeddings.

Critical issues can be resolved more quickly because to the automatic priority assignment and routing process, which also increases administrative efficiency overall. Additionally, organized data analysis and documentation are supported via the Excel-based report production capability. The suggested method improves categorization performance and offers a scalable solution for real-time complaint monitoring and management, according to experimental data.

REFERENCES

[1] Deshmukh, K. V., & Shiravale, S. S. (2018, April). Priority based sentiment analysis for quick response to citizen complaints. In 2018 3rd International Conference for Convergence in Technology (I2CT) (pp. 1-5). IEEE.
[2] Pang, B., Lee, L., & Vaithyanathan, S. (2002, July). Thumbs up? Sentiment classification using machine
[3] Xu, H., Xu, M., Deng, X., & Wang, B. (2025). Sentiment diffusion in online social networks: A survey from the computational perspective. ACM Computing Surveys, 57(12), 1-35.
[4] Toutanova K., Chang M.-W., Lee K., and Devlin J.
ArXiv preprint arXiv:1810.04805 (2018) Bert: Pre-training of deep bidirectional transformers for language understanding
[5] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, June). Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers) (pp. 4171-4186).
[6] Liu, B. (2017). Many facets of sentiment analysis. In A practical guide to sentiment analysis (pp. 11-39). Cham: Springer International Publishing.
[7] Jurek, A., Mulvenna, M. D., & Bi, Y. (2015). Improved lexicon-based sentiment analysis for social media analytics. Security Informatics, 4(1), 9.
[8] Saeidi, M., Bouchard, G., Liakata, M., & Riedel, S. (2016, December). Sentihood: Targeted aspect based sentiment analysis dataset for urban neighbourhoods. In Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers (pp. 1546-1556).
[9] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30.
learning techniques. In Proceedings of the 2002 conference on empirical methods in natural language processing (EMNLP 2002) (pp. 79-86).
Wilson, T., Wiebe, J., & Hoffmann, P. (2005, October). Recognizing contextual polarity in phrase-level sentiment analysis. In Proceedings of human language technology conference and conference on empirical methods in natural language processing (pp. 347-354).
Irsoy, O., & Cardie, C. (2014, October). Opinion mining with deep recurrent neural networks. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 720-728).
Pooria S., Gelbukh A., Ku L.-W., Gui C., and Cambria E. Proceedings of the second symposium on natural language processing for social media (SocialNLP), 2014, 28–37, A rule-based method for extracting aspects from product reviews.
[10] S. Reddy and K. Kumar, BERT and NLP Techniques for Sentiment Analysis in Retail, International Journal of Scientific Research in Computer Science, Engineering, and Information Technology (IJRSCSEIT), 2024.
[11] M Kaliappan, E Mariappan, MV Prakash, B Paramasivan, Load Balanced Clustering Technique in MANET using Genetic Algorithms.. Defence Science Journal 66 (3), 251-258.
[12] M Sivaram, M Kaliappan, S J Shobana, Prakash, V Porkodi Secure storage allocation scheme using fuzzy based heuristic algorithm for cloud, Journal of Ambient Intelligence and Humanized Computing, pp.1-9
[13] Vimal, S., Robinson, Y. H., Kaliappan, M., Vijayalakshmi, K., &Seo, S. (2021). A method of progression detection for glaucoma using K-means and the GLCM algorithm toward smart medical prediction. The Journal of Supercomputing, 77(1), 1–17. https://doi.org/10.1007/s11227-020-03268-0
[14] Kaliappan M, Guruprakash B, Rajalakshmi, J. Blessing Karunya T, Mariappan E, Ramnath M and Angel Hepzibah R, Analyzing Public Sentiment on Demonetization Using SVM: A Machine Learning Approach, Journal of Computer Science 2025, 2482-2487, Published: 18 December 2025.
[15] Hasan S, Piran J, Shamsuddin SM, and Abdi A (2019)
multi-feature fusion-based sentiment classification of evaluative text using deep learning.
[16] Liu, X., He, P., Chen, W., & Gao, J. (2019, July). Multi-task deep neural networks for natural language

[17] understanding. In Proceedings of the 57th annual meeting of the association for computational linguistics (pp. 4487-4496).
[18] Umer, Q., Liu, H., & Sultan, Y. (2018). Emotion based automated priority prediction for bug reports. IEEE Access, 6, 35743-35752.

[19] Wang, X., Jiang, Y., Bach, N., Wang, T., Huang, Z., Huang, F., & Tu, K. (2020, November). More embedding, better sequence laborers?. In Findings of the Association for Computational Linguistics: EMNLP 2020 (pp. 3992-4006).
[20] Adesam, Y., & Berdičevskis, A. (2021). Part-of-speech tagging of Swedish texts in the neural era. In Proceedings of the 23rd Nordic Conference on Computational Linguistics (NoDaLiDa) (pp. 200-209).
[21] Tortoni, A., Shirvani, R. A., Keneshloo, Y., Tavares, N., & Fox, E. A. (2020). Natural language processing advancements by deep learning: A survey. arXiv preprint arXiv:2003.01200.
[22] Paul, R., Imam, M. H., & Mou, A. J. (2023). Ai-powered sentiment analysis in digital marketing: A review of customer feedback loops in it services. American Journal of Scholarly Research and Innovation, 2(02), 166-192.