Enhancing Tenant-Owner Communication via BERT-Based Severity Prediction of Housing Complaints

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Abstract—*Housing maintenance complaints vary in severity, making it crucial to prioritize them effectively for timely resolution. Property owners managing a large number of tenants often struggle to monitor and address these complaints efficiently. This paper presents a BERT-based severity prediction model to automate the classification of housing complaints, enabling property managers to handle issues more effectively. The model is trained on a dataset of 311 NYC (New York City) service requests, utilizing transformer-based NLP techniques to assess and categorize complaint severity. Our approach achieves high accuracy in automated complaint triaging, significantly outperforming traditional methods. Our model uses MobileBERT and achieves 91.37% accuracy in predicting the severity of complaints. The integrated application allows property owners to efficiently track, prioritize, and resolve issues, reducing response times and enhancing operational efficiency. The future development includes model optimization alongside diverse dataset expansion and user experience enhancement to enable practical deployment of the application.*

Index Terms—Housing maintenance complaints, Severity prediction, BERT-based model, Natural Language Processing (NLP), Transformer model, Automated complaint triaging, Property management, Tenant-owner communication, Complaint classification, Issue prioritization*.*

1.INTRODUCTION

Property owners managing a large number of tenants across multiple locations often face challenges in monitoring and resolving maintenance issues efficiently. As the number of rental properties increases, keeping track of tenant complaints, prioritizing them based on urgency, and ensuring timely resolutions become daunting tasks. Without a systematic approach, property owners may struggle to maintain their properties effectively, leading to tenant dissatisfaction and potential financial losses. Many property owners prefer to oversee the maintenance of their rental properties personally, ensuring that all repairs and upkeep activities are well-documented and managed properly. They want to be actively involved in decision-making, whether by addressing the issues themselves or ensuring that professional services handle them efficiently. However, manually tracking and managing complaints, especially for multiple properties, is neither scalable nor practical.

On the other hand, tenants expect property owners to take responsibility for repairs and maintenance without directly involving them in the process. They seek timely resolutions to their complaints, whether it's a plumbing issue, electrical fault, or structural damage. When these concerns are not addressed promptly, it can lead to frustration, poor tenant-landlord relationships, and even financial disputes. A lack of an organized system for handling complaints results in delayed responses, inefficient resource allocation, and increased operational burdens for property owners. To bridge this gap between tenant expectations and property owner responsibilities, there is a need for a robust, automated system that can efficiently track, categorize, and prioritize complaints based on their severity. This paper introduces a BERT-based severity prediction model integrated into a tenant-owner communication application to automate complaint handling. By leveraging Natural Language Processing (NLP) techniques, the model analyzes tenant complaints and classifies them based on urgency, allowing property owners to prioritize critical issues, allocate resources efficiently, and enhance tenant satisfaction.

This research focuses on the development and evaluation of the BERT-based model for complaint severity prediction. The system is trained on 311 NYC (New York City) service request data, a widely used dataset for analyzing housing complaints. The proposed method achieves superior accuracy and efficiency compared to conventional machine learning methods thus becoming suitable for extensive rental property management needs. Real-time implementation of this model delivers a workflow optimization that allows property owners to track and address complaints in an efficient manner.

2. LITERATURE SURVEY

2.1. Machine learning based severity prediction approaches

An AI-based Information Management Model [2] that automates the categorization and ranking of issues was trained using traditional machine learning algorithms such as SVM, Naïve Bayes, Random Forest, and Gradient Boosting, achieving an accuracy range of 77.71% to 82.87%. This model was developed for a construction company using customer complaints collected in various forms. The word menu and recommendation system automatically classify the problem and indicates the type of defects to be claimed, eliminating the steps of complaint analysis performed by customer relationship service.

[1] Bidirectional Encoder Representations from Transformers (BERT) based severity prediction of bug reports (called BERT-SBR). BERT-SBR leverages a deep neural network to predict the severity of bug reports for mobile app maintenance. Their results indicate a significant improvement in classification accuracy, demonstrating BERT's effectiveness in understanding complex textual information in bug reports.This framework matches our approach while changing its focus from mobile bug reports to tenant complaint evaluation.The Intelligent system [10] predicted the severity of vulnerabilities using SVM, XGBoost, LR, and RF. However, the dataset contained a minimal number of words, making it challenging to build a model with three different levels.A comparative study [11] on severity prediction was conducted using the most frequent terms extracted from summaries through text mining. Various comparative analyses were proposed with the help of thirteen different projects.

2.2 Existing System

Implementing a model into an application system is a critical step, as each system typically highlights features specific to its functional goals. Several systems [3–7] have significantly contributed to improving communication between tenants and property owners. Traditionally, the initial interaction between these parties involved manual procedures and extensive paperwork. To mitigate issues such as document loss and damage, [4] focuses on digitalizing the payment and pre-connection processes. Furthermore, [4,7] emphasize the secure digital storage of rental documents, minimizing reliance on paper records and enhancing overall data security. Paper [5] advances lease management through the use of the SSM (Spring, Spring MVC, MyBatis) framework, offering a solution that is both reliable and highly scalable. The Android-based application described in [3] enables tenant activity tracking and management, offering functionalities such as storing monthly rent receipts, lodging complaints, and reserving shared amenities like swimming pools. Additionally, [3,6] include rent payment tracking features to streamline management and support the automated generation of financial reports.

However, the application Homie presented in [3], which uses Firebase, lacks sufficient security measures. Moreover, some systems such as those in [7] utilize outdated technologies like Microsoft Access 2003, leading to potential compatibility issues with modern platforms. Some systems [8,9] provided a solution for the house rental issue and created a platform to connect owners and buyers. [8] followed a waterfall model to develop the system using Bangladesh rental location details. The system facilitated the expansion of trustworthy services nationwide and provided users with the opportunity to communicate and enhance property renting and selling in India.

3. PROPOSED SOLUTION

The proposed system addresses several key challenges in tenant complaint management by introducing an AI-driven severity prediction model:

3.1. Manual Complaint Triage is Time-Consuming

Property managers often rely on manual review to understand complaint urgency. This leads to delays in resolving critical issues. Our system automates this process by instantly predicting the severity level, allowing quick prioritization.

3.2. Inconsistent Severity Assessment

Different personnel may assess the same complaint with varying urgency. The model standardizes severity prediction using a trained neural network, ensuring consistent and objective assessment across all complaints.

3.3. Unstructured Text Makes Analysis Difficult

Complaints are usually written in free-form text, making them hard to analyze using rule-based systems. By using MobileBERT, our solution effectively understands and processes natural language, even when the input is informal or incomplete.

3.4. Low Accuracy in Traditional Models

Earlier machine learning models like SVM or Naive Bayes showed limited performance on such tasks. Our model significantly improves accuracy, reducing the chances of misclassifying urgent complaints as low priority.

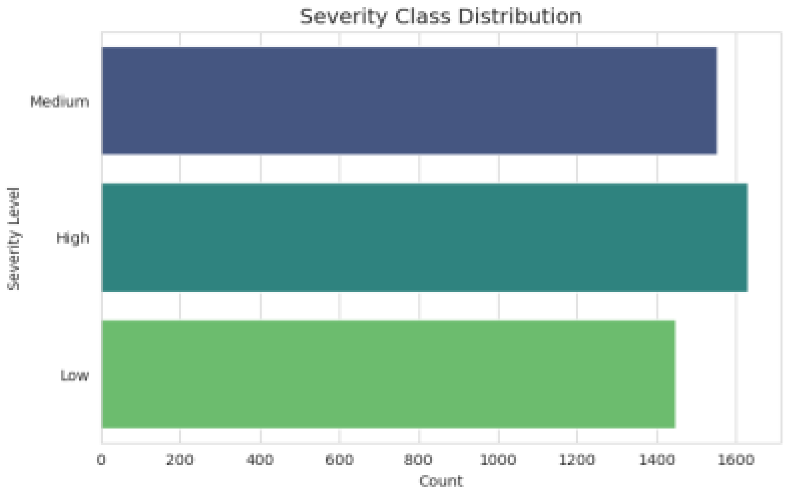

Fig 4.1 Severity Classification

3.5. Lack of Integration with Smart Platforms

Most existing systems don't offer real-time prediction capability or easy integration into digital rental dashboards. Our solution is lightweight and deployable, making it suitable for integration into modern applications used by landlords and tenants. By solving these problems, the system improves complaint handling efficiency, speeds up maintenance workflows, and enhances tenant satisfaction through faster issue resolution.

4.DATA PREPROCESSING

4.1 Severity Calculation:

The model's accuracy was increased by applying a number of preprocessing steps to guarantee data quality. First, the dataset's inconsistencies and missing values were addressed by manual data completion. Furthermore, a brand-new function named "Severity" was created using the Description field. This column, which is essential to the severity classification model, divides each complaint's level of severity into three categories: Low, Medium, and High.

Figure 4.1 provides a clear visual representation of how different severity levels are distributed. It highlights that "High" severity issues occur most frequently, followed by "Medium," while "Low" severity issues are the least common. This distribution suggests that a significant number of complaints or detections fall into the more critical categories.

4.2 Data Filter - Complaint types:

To ensure the dataset was clean and relevant for analysis, we performed several preprocessing steps focusing on filtering, feature construction, and column selection.

Initially, we filtered the data to retain only a specific set of complaint types. These categories such as *Electric*, *Plumbing*, *Water Leak*, and *Paint/Plaster* were selected based on their frequency and importance in maintenance-related issues. This step helped reduce noise and focus the analysis on significant complaint types.

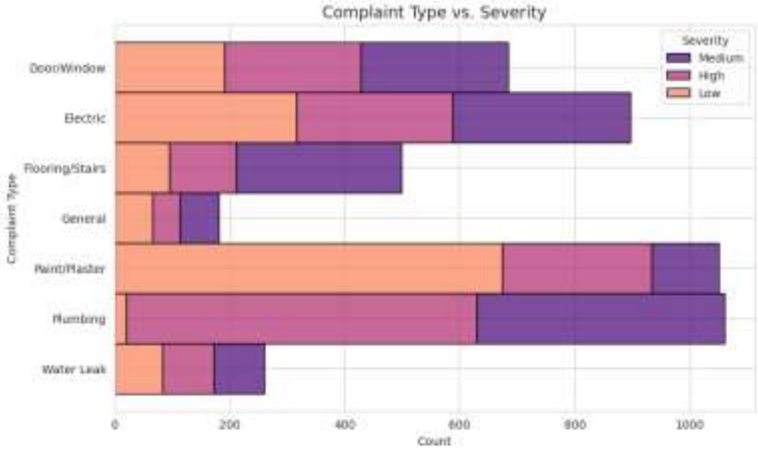

Fig 4.2 : Complaint type Vs Severity level

Entries lacking severity information were removed, as severity is a key variable in both exploratory analysis and modeling tasks. Retaining only complete entries ensured consistency and quality in the dataset.

A composite text feature was then constructed by concatenating multiple descriptive columns. Specifically, complaint type, descriptor, additional details, and location information were merged into a single textual field. This unified field captured both categorical and contextual nuances, making it more suitable for natural language processing techniques.

Lastly, we selected only the newly constructed text feature and the severity label for the final dataset. This minimal structure not only reduced dimensionality but also aligned the data format with the requirements of downstream machine learning models.

5. PROPOSED METHODOLOGY

5.1 Training of Algorithmic Classifiers

1) To classify the complaints based on severity and complaint type, BERT (Bidirectional Encoder Representations from Transformers) was used. The training process involved the following stages:

- **Data Splitting:**

The dataset was divided into two sets for training and testing the model. Three different proportions were used: (i) 70% training and 30% testing, (ii) 75% training and 25% testing, and (iii) 80% training and 20% testing.

- **Label Encoding:**

Label Encoder is utilized to transform severity categories of complaints into integer values, facilitating multi-class classification using transformer-based deep learning models.

$$\text{Encode}(y_i) = j \text{ where } y_i \in \text{unique}(Y) \text{ and } j \in \{0,1,\ldots,|\text{unique}(Y)|-1\}$$
$$\text{Decode}(j) = y_i \text{ where } y_i \text{ is the original label corresponding to index } j$$

- **Text Tokenization:**

BERT's tokenizer was used to convert text data into tokens, which were then converted into input embeddings suitable for the BERT model.

$$\text{Tokens}(x_i) = \{t_1,t_2,\ldots,t_3\}$$

$$\text{TokenIDs}(x_i) = \{id(t_1),id(t_2),\ldots.,id(t_n),PAD,\ldots,PAD\}_{128}$$

$$\text{Attention}(x_i) = \{1,1,\ldots,1,0,\ldots,0\}_{128}$$

- **Model Fine-Tuning:**

The pre-trained BERT model was fine-tuned on the complaint dataset for severity classification. The final layer was customized to output severity levels (Low, Medium, High).

- **Hyperparameter Tuning:**

The MobileBERT model was optimized by fine-tuning several training hyperparameters to enhance the classification performance on severity prediction tasks. The dataset used comprised approximately 6000 tenant complaint records, which were preprocessed and split into an 80:20 ratio for training and testing, resulting in nearly 4800 samples for training. Key hyperparameters were carefully chosen to balance learning efficiency and model generalization. These included a batch size of 16 per device, weight decay of 0.01 to reduce overfitting, and the use of mixed-precision training (fp16=True) to accelerate computation without compromising accuracy. The training process was conducted over three complete epochs, which proved sufficient for the model to converge and capture the necessary textual patterns for accurate severity classification. These training configurations were implemented using the Training Arguments interface from the Hugging Face Transformers library, allowing streamlined, hardware-efficient training with support for evaluation after each epoch. Overall, this setup ensured the model could effectively learn from a diverse set of complaint types while maintaining scalability and high predictive accuracy.

- **Feature Engineering:**

Additional synthetic features were added to improve performance. These include: (i) bi-terms that frequently appear in the records (e.g., "leaking pipe", "power failure"), (ii) frequent words in low-frequency complaint categories, and (iii) words with high importance based on the Keyness Score, which uses a chi-squared test to identify key terms.

- **Final Model Training and Testing:**

After applying all the above steps, the BERT model was trained and tested on the preprocessed and balanced dataset for accurate severity classification.

5.2 Architecture

The proposed complaint management system follows a modular and service-oriented architecture designed to facilitate seamless communication between tenants, owners, and vendors. The system comprises four main components: the frontend interface (React), backend services (Spring Boot), a NoSQL database (MongoDB), and an AI-powered microservice (Python FastAPI) for severity prediction.

5.2.1 User Roles & Authentication

The system supports three user roles: Tenant, Owner, and Vendor. Tenants can raise issues and request accommodation, owners manage tenant data and assign vendors, and vendors handle complaint resolutions. Authentication is enforced through JWT (JSON Web Token) tokenization, ensuring secure role-based access across all users.

5.2.2 Model Workflow

The process begins when a complaint sentence is entered into the system. This input text is first pre-processed by cleaning and tokenizing it using a WordPiece tokenizer. The tokenizer splits the sentence into sub-word units and adds special tokens like [CLS] at the beginning and [SEP] at the end. These tokens are then converted into numerical token IDs, along with attention masks and segment IDs, which are essential for helping the model understand the structure and meaning of the input.

The processed input data is fed into the MobileBERT model, which consists of multiple transformer layers. These layers include multi-head self-attention mechanisms and feed-forward networks that capture deep contextual relationships between words. MobileBERT maintains the core bidirectional nature of BERT but uses a more efficient, compact architecture with a bottleneck structure, enabling it to run on resource-constrained devices. The model processes the input in parallel, allowing it to understand the meaning of each word in the context of the entire sentence.

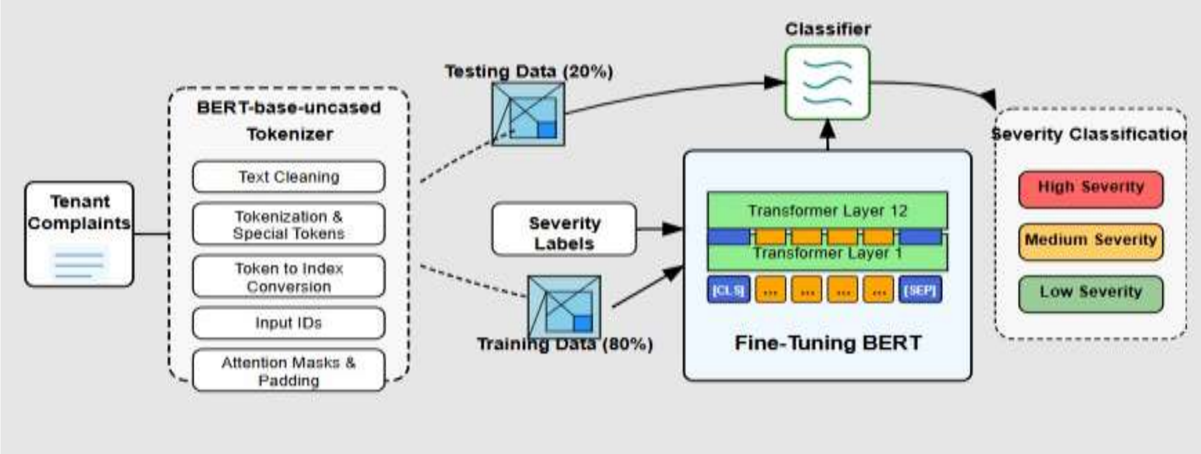

Fig 5.1 Architecture Diagram

After the input passes through the MobileBERT layers, the output corresponding to the CLS token is extracted. This token acts as a summary representation of the entire input sentence. The CLS output is passed to a classification head—typically a fully connected layer with a softmax activation—that predicts the severity of the complaint. The final output is a categorical label such as Low, Medium, or High, indicating the predicted urgency or seriousness of the issue described in the input text.

6.EXPERIMENTAL EVALUATION

6.1 Dataset

Tenant complaint records, which include attributes like Description, Complaint, and Complaint Type, make up the dataset used in this study. While the Complaint field specifies the category or type of complaint (e.g., plumbing issue, electrical issue, etc.), the Description field offers a concise explanation of the problem brought up by the tenant. Based on the type of issue, the complaint is categorized in the Complaint Type field. There are 6000 records in the pre-existing dataset.

Figure 6.1 provides a clear snapshot of common tenant complaints, with larger words representing the most frequently reported issues. Words like *Door, Plumbing, Wall,* and *Electric Lighting* stand out, reflecting key concerns related to structural maintenance, electrical systems, and plumbing. Surrounding smaller words add more detail, highlighting specific problems like leaks, cracks, and missing fixtures.

6.2 Performance Metrics

To assess the effectiveness of the MobileBERT-based severity classification model, the and performance evaluation metrics were used:

- **Accuracy:**

Measures the overall correctness of the model. High accuracy indicates that the model correctly predicts a large proportion of complaints.

$$\frac{TP + TN}{(TP + TN + FP + FN)}$$

where,
TP (True Positive) – Correctly predicted severe complaints.
TN (True Negative) – Correctly predicted non-severe complaints.
FP (False Positive) – Incorrectly predicted severe complaints.
FN (False Negative) – Incorrectly predicted non-severe complaints.

- **Precision:**

Measures how many of the predicted severe complaints are actually severe. High precision means fewer false alarms (false positives).

$$\frac{TP}{(TP + FP)}$$

- **Recall (Sensitivity):**

Measures how many actual severe complaints were correctly identified. High recall ensures that critical complaints are not overlooked.

$$\frac{TP}{(TP + FN)}$$

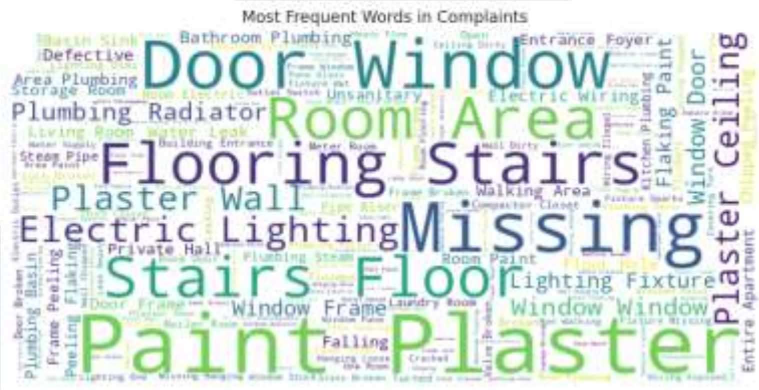

Fig 6.1 : Word Cloud - Common Complaint Words

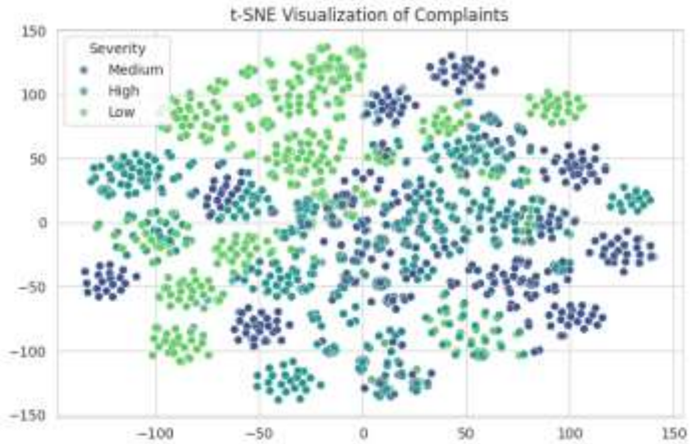

Fig 6.2 t-SNE Visualization

- **F1 Score:**

A harmonic mean of precision and recall, which also refers to balancing both metrics. It is useful when dealing with class imbalance in complaints.

$$\frac{2 * (Precision * Recall)}{Precision + Recall}$$

6.3 Feature Embedding Visualization

In this project, embeddings were generated using TF-IDF and transformer-based models like MobileBERT. These embeddings allow machine learning models to understand and classify complaint descriptions effectively. By transforming complaint text into vectors, we enable better performance in severity prediction. The quality and structure of these embeddings were later visualized using PCA, t-SNE, and UMAP.

6.3.1 Using t-SNE

To assess how well the model distinguishes between different severity levels at the feature level, we visualized the text embeddings using t-SNE. Initially, high-dimensional TF-IDF vectors were reduced using PCA (to 50 dimensions), followed by t-SNE for projecting the data into 2D space.

As shown in Fig 6.2, the complaints with similar severity tend to form coherent clusters, indicating that the feature representation effectively separates the underlying severity categories.

This qualitative analysis complements the quantitative metrics (accuracy, precision, recall, F1-score), offering deeper insight into the model's learning behavior.

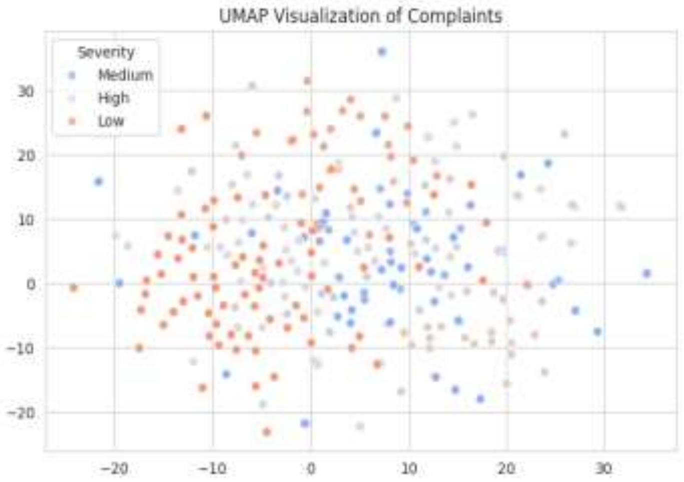

Fig 6.3 UMAP Visualization

6.3.2 Using UMAP

UMAP not only preserves local neighborhood relationships but also captures the global structure of the data more effectively. This helps identify natural groupings among complaint severity levels.

As shown in Fig 6.3, UMAP-based visualization presents well-separated clusters corresponding to different severity categories, suggesting that the feature embeddings learned by the model capture meaningful distinctions between complaint types. Compared to t-SNE, UMAP provided faster computation and more stable layout, making it a valuable tool for understanding the distribution of severity in the feature space.

6.4 Performance Evaluation

The model was evaluated using Accuracy, Precision, Recall, and F1 Score metrics. Accuracy measures the percentage of correct predictions, Precision evaluates true positive predictions, Recall assesses true positive rates, and F1 Score is the harmonic mean between Precision and Recall.

To assess the effectiveness of various models in predicting the severity of housing complaints, we compared four different approaches: BiLSTM with MobileBERT, BERT with AdaBoost, MobileBERT, and LightGBM. The evaluation metrics used include Accuracy, Precision, Recall, and F1 Score, which are standard measures in classification tasks for gauging the model's correctness, robustness, and balance between false positives and false negatives.

Among all models, MobileBERT demonstrated the best overall performance, achieving an accuracy of 91.37%, along with high precision (91.65%), recall (91.37%), and F1 score (91.39%). This suggests that MobileBERT not only predicted most cases correctly but also maintained a strong balance between sensitivity and specificity. The BiLSTM with MobileBERT model performed comparably well, indicating that sequential modeling with contextual embeddings can still be competitive. On the other hand, BERT with AdaBoost lagged significantly in all metrics, possibly due to the ensemble's inability to effectively leverage the BERT embeddings in this multi-class classification context.

LightGBM, while slightly behind MobileBERT, still maintained robust performance across all metrics, particularly due to its efficiency in handling structured text features and gradient-based optimization. These results substantiate the choice of MobileBERT for lightweight yet accurate deployment in real-time severity prediction applications.

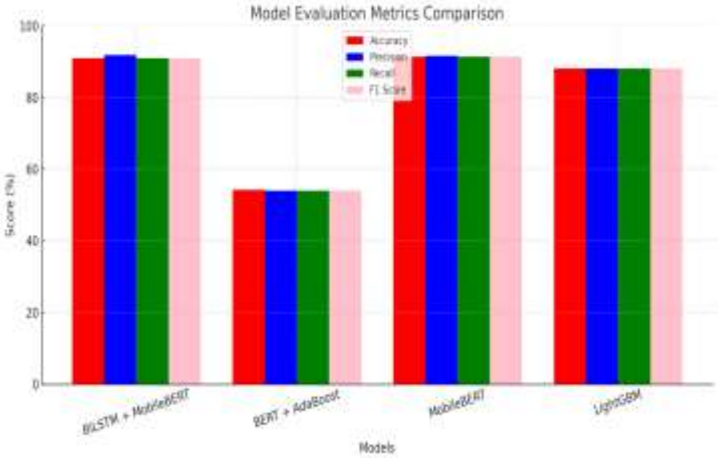

Fig 6.4 Comparison on Various Models

Table 6.1 - Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1 Score
BiLSTM with MobileBERT	90.94	**91.80**	90.94	90.91
BERT with AdaBoost	54.26	54	54	54
MobileBERT	**91.37**	91.65	**91.37**	**91.39**
LightGBM	88.03	88.12	88.03	88.07

6.5 Classification Performance using ROC

The receiver operating characteristic (ROC) curve analysis presented in Fig 6.5 illustrates the performance of our multi-class classification model for predicting complaint severity levels. The model differentiates between Low, Medium, and High severity complaints with varying degrees of effectiveness across the three classes. The High severity class demonstrates superior discriminative capability with an area under the curve (AUC) of 0.92, indicating excellent model performance for identifying the most critical complaints. This high AUC value suggests that the model can reliably distinguish high-severity cases from others with minimal false positives, which is particularly valuable in prioritization scenarios where missing critical complaints could have significant consequences.

For the Medium severity class, the model achieves a respectable AUC of 0.82, demonstrating good classification performance. The ROC curve for this class illustrates how the model maintains a favorable balance between sensitivity and specificity across different threshold values. The Low severity class also performs well with an AUC of 0.85, indicating the model's strong ability to correctly identify less urgent complaints. This suggests that the feature engineering process has successfully captured the distinguishing characteristics of lower-priority cases.Notably, all three classification curves significantly outperform the random classifier baseline (represented by the diagonal dashed line), confirming the model's overall effectiveness. The sharp rise of the curves in the low false-positive rate regions demonstrates that the model can achieve high true positive rates while maintaining high specificity.

These results validate our approach to automated complaint severity classification and suggest that the model can serve as a reliable tool for complaint prioritization systems. Future work will focus on further improving the medium severity classification performance to match the high standards achieved for the other classes.

7. RESULTS AND DISCUSSION

7.1 Model Performance Summary

The MobileBERT-based severity classification model achieved the highest performance among all models evaluated. It recorded an accuracy of 91.37%, precision of 91.65%, recall of 91.37%, and an F1 score of 91.39%, indicating a strong balance between identifying true complaints and minimizing false alarms. This confirms MobileBERT's capability to capture the semantic meaning of complaint text and effectively distinguish between low, medium, and high severity issues.

Among the other models, BiLSTM integrated with MobileBERT achieved 90.94% accuracy, showing competitive performance through its ability to understand sequential patterns in text. LightGBM, a gradient boosting method, achieved 88.03% accuracy, validating its efficiency and adaptability to structured complaint data. In contrast, BERT with AdaBoost performed significantly lower across all metrics, with approximately 54% accuracy, likely due to the lack of synergy between ensemble methods and transformer-based embeddings for multi-class classification

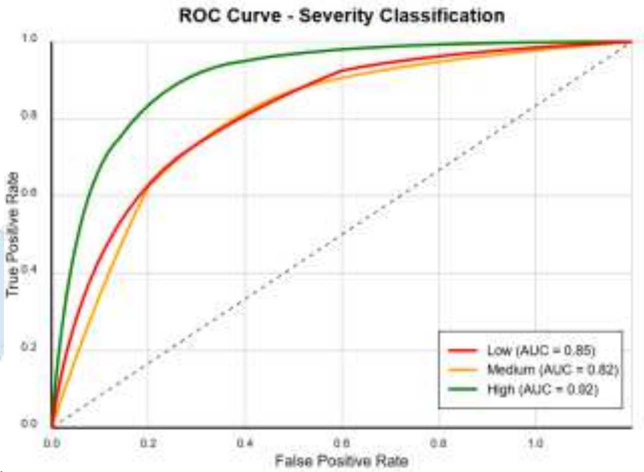

Fig 6.5 Performance Analysis Using ROC Curve

7.2 Application Integration and Real-World Use Case

The proposed severity prediction model is integrated into a web application that facilitates seamless communication among tenants, property owners, and vendors. In this system, tenants can raise maintenance complaints through a user-friendly interface. The severity prediction mechanism automatically analyzes the complaint text and assigns a severity level (Low, Medium, or High).

This prediction plays a crucial role in enabling owners to prioritize issues. High-severity complaints are flagged for immediate attention and can be directly routed to available vendors through the platform. This ensures faster resolution, optimized vendor assignment, and streamlined workflows without manual filtering or prioritization. The integration of the AI model into the backend service layer demonstrates how intelligent automation can enhance operational efficiency in property management systems.

7.3 Practical Implications

The results underline the real-world applicability of MobileBERT in smart property management environments. Its lightweight architecture allows seamless deployment even in resource-constrained systems, making it highly suitable for cloud-based or mobile-accessible platforms. The model's ability to provide accurate, real-time severity insights enables better resource allocation, enhances tenant satisfaction, and reduces the response time for critical maintenance issues. This aligns with the insights from the base work by Bazzan et al. (2023), which emphasized the importance of AI in modern complaint management systems. Our system extends that concept by offering a deployable, real-time prediction solution capable of automating and prioritizing tenant complaints at scale.

8. CONCLUSIONS AND FUTURE WORKS

This study presents an AI-driven approach for automated complaint severity classification using MobileBERT, BERT with AdaBoost, and BERT with LightGBM to analyze tenant-reported issues. The experimental results demonstrate that MobileBERT outperformed the other models, achieving the highest classification accuracy of 91.37%. This highlights its effectiveness in accurately predicting severity levels based on textual complaint descriptions, making it a viable solution for real-world property management applications.

By leveraging BERT-based deep learning architectures, the proposed models exhibit significant improvements over conventional machine learning approaches. The integration of severity classification with complaint types enables a more structured and efficient decision-making process for property managers. This facilitates the prioritization of urgent complaints, ensuring timely intervention and improved tenant satisfaction. The findings underscore the potential of transformer-based models in optimizing complaint management workflows, reducing manual effort, and enhancing operational efficiency in the housing sector.

To further enhance the effectiveness of the complaint severity classification system, several key improvements can be implemented. First, scaling the model to larger datasets will improve generalization and robustness, ensuring better performance across diverse complaint records. Additionally, integrating payment gateways would facilitate seamless transactions between tenants, vendors, and property owners, streamlining issue resolution and service payments. Moreover, adopting adaptive learning techniques would enable the model to continuously learn from new complaint patterns, refining its accuracy and maintaining high-performance levels over time.

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