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Scalable Customer Support Ticket Analysis Using Hybrid NLP and Ensemble-Based Classification Models

Bulusu Rama[1*], Ponthati Praveen Reddy[2], Bollapalli Sai Bharath[2], Varshith Kambhampati[2]

[1]Associate Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (AI & ML),
[1,2]Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: Bulusu Rama (bulusurama1967@gmail.com)

Abstract

Customer support centres generate vast volumes of support tickets reflecting customer issues, priorities, and satisfaction levels. Accurate and timely prediction of customer satisfaction, ticket priority, and resolution outcomes from these unstructured textual data is crucial to improving service quality and operational efficiency. Traditionally, support ticket management has relied on manual assessment or basic machine learning models using shallow text features like bag-of-words or Term Frequency–Inverse Document Frequency (TF-IDF), which lack a deep understanding of context and semantics. These approaches are limited in scalability, accuracy, and the ability to handle multiple predictions simultaneously, often leading to delayed or inconsistent customer service. Motivated by these limitations and the increasing availability of large-scale support ticket data, this project proposes a hybrid machine learning framework leveraging state-of-the-art natural language processing techniques. The system preprocesses support ticket text through lemmatization, stop word removal, and part-of-speech tagging to clean and normalize input data. Using eXtreem Language Network (XLNet), a powerful transformer-based language model, contextual embeddings are generated to capture semantic nuances beyond traditional feature engineering. Multiple classical machine learning classifiers including Quadratic Discriminant Analysis (QDA), Linear Discriminant Analysis (LDA), Hist Gradient Boosting (HGB), Stochastic Gradient Descent (SGD) Classifier, and Nearest Centroid (NC) are trained on these embeddings to predict three key targets: Ticket Priority, Customer Satisfaction Rating, and Resolution. The proposed multi-target classification system uniquely combines advanced text mining with a diverse set of machine learning models to improve prediction accuracy, interpretability, and robustness across varied ticket types.

Keywords: Customer Support Analytics, Multi-Target Classification, Ticket Priority Prediction, Transformer Models, XLNet, Text Mining

1. Introduction

The landscape of ticket management and monitoring is undergoing a transformative evolution, driven by advancements in Large Language Models (LLMs) and Generative AI technologies. These cutting-edge tools empower automated, context-aware ticket grouping, prioritization, and resolution recommendations that leverage established Standard Operating Procedures (SOPs) and historical support data. As a result, the traditionally manual and labour-intensive tasks of reading, categorizing, and resolving tickets are becoming streamlined, reducing cognitive load and delays for support engineers. Despite these promising transformations, organizations face significant challenges in transitioning from legacy ticket management systems to AI-powered solutions. Key hurdles include migrating trained personnel to new tools, preserving domain knowledge and intellectual property, and accurately transferring operational data such as Service Level Agreements (SLAs) and expert-driven policies into modern AI frameworks. To address these issues, our approach introduces a suite of

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application-agnostic, modular microservices tailored for ticket clustering, prioritization, resolution, data ingestion, and visualization. This flexibility allows organizations to adopt and customize features incrementally, aligning with their unique operational requirements.

Importantly, effective incident management in real-world IT Service Management (ITSM) environments extends beyond textual analysis. It must consider spatial factors like device topology and logical infrastructure, temporal aspects such as incident timing, and data provenance across heterogeneous sources. The inherently dynamic IT landscape further requires adaptive clustering methods capable of evolving cluster sizes and compositions as new data streams in. Our research bridges this gap by integrating spatial and temporal dimensions with semantic similarity algorithms to enhance ITSM ticket clustering. This enriched clustering framework captures the operational complexities of IT environments, enabling more accurate incident grouping and prioritization. By delivering a context-aware approach, this work supports improved diagnostics, optimized resource allocation, enhanced service stability, and ultimately, superior customer satisfaction.

2. Literature Survey

This literature survey reviews key research and developments in incident management, natural language processing (NLP), clustering algorithms, and AI-driven resolution systems. This context is essential to understand the contributions of incident-ai within the existing landscape of incident management solutions.

2.1 Incident Management Systems

Incident management systems are crucial in IT service management (ITSM), aiming to restore normal operations swiftly and minimize business disruptions. Traditional systems, as outlined by the ITIL framework [5], emphasize structured processes and manual ticket handling. However, these systems often struggle with high volumes of incidents and the complexity of manual categorization and resolution, leading to inefficiencies and delays. Ticket categorization and routing are critical for ensuring swift resolution, customer satisfaction, high productivity, and adherence to Service-Level Agreements (SLAs), which often require issues to be resolved within a set timeframe [9]. However, improper routing can lead to inefficient assignments and increased costs for both customers and service providers [14]. Ticket Automation (TA) systems aim to minimize the steps from ticket submission to resolution. A key function of these systems is the accurate classification of incoming tickets, essential for quickly addressing customer requests. This need has grown with the increasing volume of support tickets, particularly in IT companies, highlighting the importance of efficient automated resolution systems [3].

2.2 NLP techniques in Incident Management

Leimeister et al. [17] demonstrated an effective method to enhance classification accuracy by incorporating information from the labels' hierarchical structure into the classifier. They focus on classifying tickets using a pre-trained BERT language model, highlighting how this approach can refine categorization processes. Their study further reveals that the choice of ticket embedding strategy significantly influences classification metrics, underlining the importance of embedding selection in achieving optimal classification performance. The classification of incidents in ticketing systems typically involves assigning a priority to assess the urgency and a type to gauge the importance of the incident, such as distinguishing between an information request and an incident report [12].

2.3 Clustering Algorithms for Ticket Grouping

Clustering algorithms are vital for grouping similar incident tickets, facilitating more efficient resolution processes. Jain et al. [11] provided a comprehensive review of clustering techniques, emphasizing the importance of similarity measures. Huang et al. [10] proposed an adaptive clustering method for IT service management that considers temporal patterns and incident similarities, showcasing the benefits of dynamic clustering approaches in improving incident handling efficiency.

2.4 Hierarchical Clustering and Embedding Techniques

Hierarchical clustering is particularly relevant for incidents involving networked devices, where understanding the network topology is crucial. Murtagh and Contreras [13] reviewed hierarchical clustering algorithms, detailing their applications and advantages. Embedding techniques, such as those provided by Hugging Face BGE models, have enhanced the capability to capture semantic and hierarchical relationships in text data. Devlin et al. [7] introduced BERT, a transformer-based model that significantly improved NLP tasks, paving the way for subsequent embedding models used in various applications, including incident management.

2.5 AI-Driven Resolution Systems

AI-driven systems for incident resolution are gaining traction, with models like GPT offering advanced text generation capabilities. Brown et al. [4] described GPT-3's architecture and its potential in diverse NLP applications. The integration of GPT-3.5 in incident resolution, as explored by Radford et al. [15], demonstrates the feasibility of using AI to generate contextually relevant and accurate resolutions based on comprehensive problem categorizations.

2.6 Knowledge Bases in Incident Management

Knowledge bases support incident categorization and resolution by providing structured information on problem categories and solutions. Aamodt and Nygård [1] discussed the role of case-based reasoning and knowledge management in decision-support systems. More recent works, such as those by Fensel et al. [8], highlight the importance of structured knowledge bases in improving the accuracy and efficiency of automated ITSM systems.

Despite the extensive research and advancements in AI-driven incident management and IT service management (ITSM) platforms, several gaps remain. Current solutions, including those offered by platforms like ServiceNow, provide robust ITSM capabilities but often lack the dynamic adaptability and deep contextual understanding required for optimal incident clustering and resolution. Existing literature points to the need for more sophisticated AI integration, dynamic clustering parameters, organization-specific customization, and proactive incident management. However, there is limited exploration into a comprehensive AI-driven system that combines these aspects to provide a seamless, adaptive, and highly efficient incident management solution.

2.7 Research Gaps

1. **Limited Dynamic Adaptability in Current Systems**: Most existing ITSM platforms and traditional incident management systems follow static, rule-based ticket routing and classification methods. They lack the ability to dynamically adapt clustering parameters and model ecisions in real-time based on evolving incident patterns and organizational context.
2. **Scarcity of Organization-Specific Customization**: Current AI-driven incident resolution tools often overlook the importance of tailoring models and clustering strategies to

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organization-specific policies, workflows, and historical incident characteristics. This lack of customization limits the effectiveness and acceptance of AI solutions across diverse enterprises.

3. **Inadequate Proactive Incident Resolution Capabilities**: Existing solutions primarily focus on reactive incident management. There is a notable gap in systems that proactively predict incident escalations or resolutions by integrating advanced AI components, such as generative models, and knowledge bases to suggest actionable next steps.
4. **Limited Holistic Systems Combining Multiple AI Components**: While studies have explored individual components such as clustering algorithms, NLP embeddings, and AI-driven resolution there is a lack of research demonstrating an integrated system that harmonizes dynamic clustering, deep contextual learning, organizational customization, and AI-generated resolution strategies within a unified framework.
5. **Sparse Utilization of Comprehensive Knowledge Bases**: Despite knowledge bases being acknowledged as crucial for ITSM decision support, relatively few studies effectively incorporate structured and case-based knowledge management within AI-driven automated incident management systems.

Addressing these gaps, the proposed system aims to architect a comprehensive, adaptive AI-driven incident management platform that seamlessly integrates XLNet transformer embeddings, hybrid machine learning classifiers, and organizational customization to improve incident triage and resolution efficiency significantly.

3. Proposed System

The proposed system is an innovative approach to transforming traditional support ticket management by integrating advanced NLP techniques, large language models like XLNet, and hybrid machine learning models. It aims to improve the efficiency and accuracy of incident handling, prioritization, and resolution in IT Service Management (ITSM) as shown in figure 1.

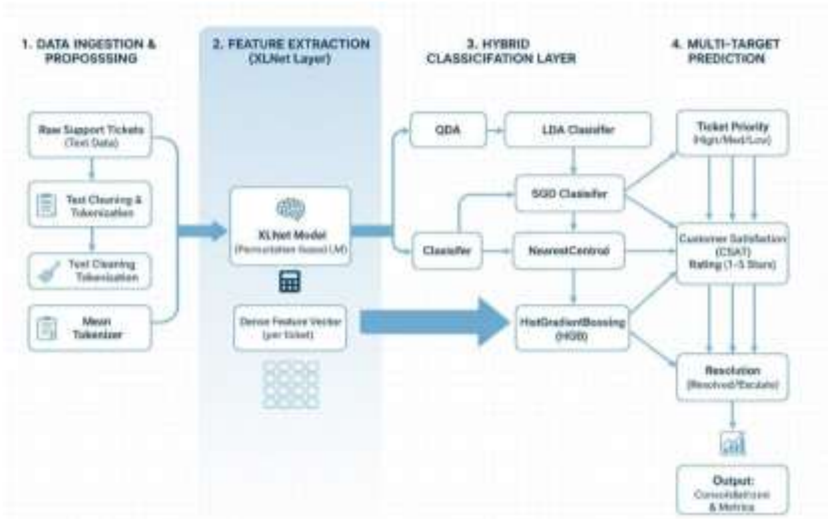

Figure. 1: Proposed system architecture

The key components and workflow of proposed system is as follows:

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Data Ingestion and Preprocessing: The system begins with comprehensive data collection from various sources, including textual descriptions of customer issues and metadata like issue type and timestamps. Preprocessing involves cleaning the text data, removing noise, tokenization, lemmatization, and stop-word removal to prepare it for analysis.

Feature Extraction Using XLNet: The cleaned text is then fed into XLNet, a state-of-the-art transformer-based language model, to generate detailed contextual embeddings. These embeddings capture semantic nuances and contextual relationships within customer tickets, providing a rich, high-dimensional feature set.

Clustering and Incident Relationship Analysis: To understand dependencies and relationships among tickets, the system combines spatial and temporal data with the semantic embeddings. This results in dynamic, adaptive clustering that reflects the real-world complexities of IT environments, such as device topology, incident timing, and data source provenance.

Model Training and Multi-Target Prediction: Multiple classical machine learning algorithms such as QDA, LDA, HGB, and others are trained on the XLNet embeddings for three core targets: Ticket Priority, Customer Satisfaction Rating, and Resolution. These models utilize the rich features to predict outcomes accurately, improving incident response times and quality.

Visualization and Insights: The system incorporates visualization modules that generate dashboards and reports, offering insights into ticket patterns, sentiment analysis, and incident dependencies. These analytics support decision-making, resource allocation, and process optimization.

Significance and Innovation

This system marks a significant advancement over conventional ticketing solutions by embedding deep contextual understanding and real-time data integration. Its innovative multi-dimensional clustering, adaptive learning capabilities, and semantic-rich features enable support teams to diagnose issues more accurately, prioritize tickets effectively, and deliver superior customer service. The modular, application-agnostic architecture allows organizations to adopt and scale this solution seamlessly, transforming support operations into a proactive, intelligent ecosystem that enhances service stability and customer satisfaction.

3.1 XLNet model

XLNet is a powerful autoregressive transformer model that improves upon traditional language models by enabling the model to learn bidirectional context via permutation-based training. Unlike BERT, which uses masked language modelling, XLNet predicts words in a randomized order, allowing it to capture dependencies in both directions without masking-related training discrepancies as shown figure 2. The key internal components and steps of XLNet are as follows:

Step 1. Input Representation

- Inputs are tokenized into WordPiece token IDs.
- Positional encodings are added to tokens to provide order information.
- Segment embeddings differentiate between sentence pairs if used.

Step 2. Transformer Layers (Self-Attention)

- XLNet uses multi-head self-attention layers that compute contextualized embeddings by attending to all positions in the input sequence.
- The attention mechanism allows modelling dependencies regardless of token distances.

Step 3. Permutation Language Modelling

- Instead of processing tokens strictly left-to-right or masking tokens, XLNet generates random permutations of the input sequence.
- For each permutation, XLNet predicts the token by conditioning on all tokens preceding it in that permutation order.
- This method allows the model to learn from all possible contexts bidirectionally while preserving the autoregressive property.

Step 4. Segment Recurrence and Relative Positional Encoding

- XLNet introduces a segment recurrence mechanism to model long-term dependencies beyond fixed-length sequences.
- Instead of absolute positional embeddings, relative positional encodings are used, improving generalization to unseen sequence orders.

Step 5. Output Layer

- The transformer's final hidden states are used to predict the next token probabilities in the permutation order during training.
- During feature extraction (in your project), the model outputs token embeddings that are pooled (mean or CLS token) to generate fixed-length vector representations.

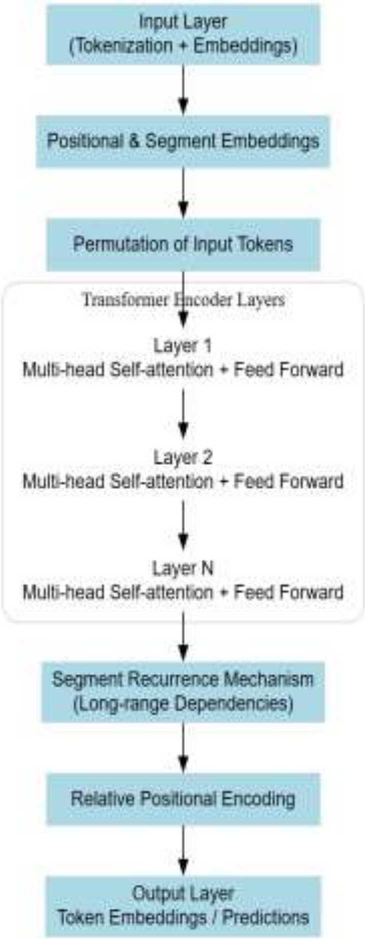

Figure. 2: The layered architecture of the XLNet model.

4. Results and Discussion

The Results and Discussion section presents the findings of the study and interprets their significance in relation to the research objectives. It combines both the data obtained and the analysis required to explain observed trends, patterns, and relationships. The results are typically organized in a logical sequence, supported by tables, graphs, or figures for clarity. In this section, the focus is not only on

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what was found but also on why those findings occurred. Comparisons with previous studies or expected outcomes help establish the validity and relevance of the results. Any unexpected observations are also examined to provide possible explanations. This section plays a crucial role in linking the experimental outcomes to theoretical concepts.

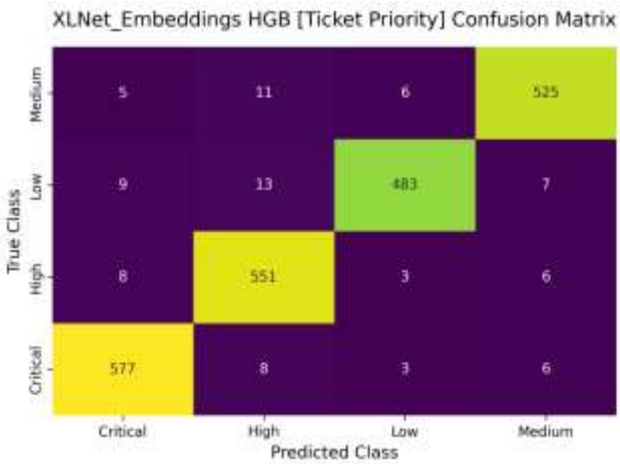

Figure. 3: Confusion matrix obtained using HGB classifier for column ticket priority.

Figure 3 presents the confusion matrices for the "Ticket Priority" classification task HGB Classifier the HGB classifier produces the best confusion matrix, with very strong diagonal dominance across all classes. Nearly all tickets are correctly classified, especially in the Critical (577/594), High (551/570), Low (483/512), and Medium (525/547) categories, demonstrating excellent discriminative power and confirming HGB as the superior model for ticket priority prediction using XLNet embeddings.

Figure. 4: Confusion matrix obtained using HGB classifier for column customer satisfaction rating.

Figure 4 displays the confusion matrices for the multi-class Customer Satisfaction Rating prediction task (5 rating levels, presumably 1 = Very Dissatisfied to 5 = Very Satisfied) using the HGB Classifier the HGB classifier produces an exceptionally strong confusion matrix with dominant diagonal elements across all five rating levels (e.g., 420/429 for rating 1, 421/440 for rating 2, 442/462 for rating 3, 412/426 for rating 4, and 443/458 for rating 5). Very few off-diagonal misclassifications occur, and most errors are limited to adjacent classes, demonstrating outstanding discriminative power and establishing HGB as the clearly superior model for predicting customer satisfaction ratings using XLNet embeddings.

Figure 5 presents the confusion matrices for the multi-class resolution prediction task HGB Classifier the HGB classifier produces an exceptionally strong and clean confusion matrix with dominant diagonal elements across nearly all resolution categories (e.g., high correct counts for Software bug, Product setup, Product recommendation compatibility, Hardware issue, Network problem support, Payment issue, Delivery problem, Cancellation request, etc.). Off-diagonal values are minimal and mostly limited to closely related categories, confirming the proposed HGB model's outstanding performance and clear superiority in accurately predicting resolution types from XLNet embeddings.

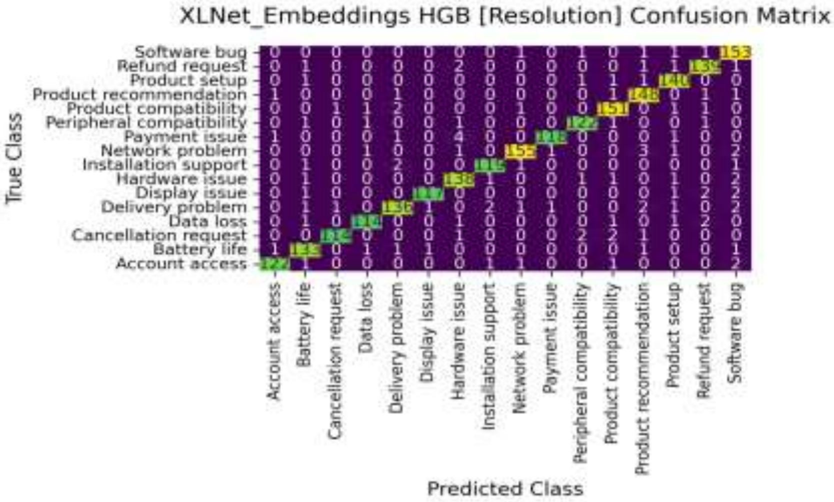

Figure. 5: Confusion matrix obtained using HGB classifier for column resolution.

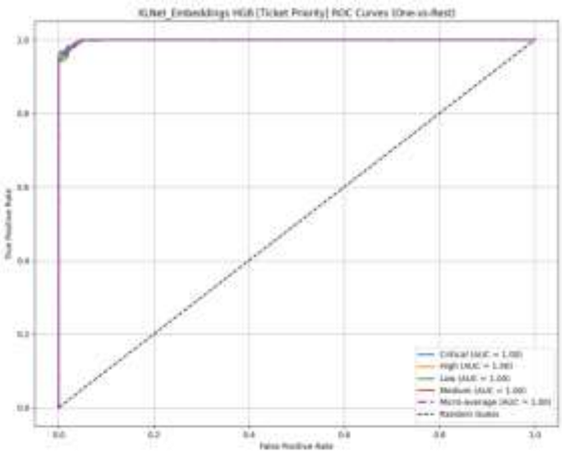

Figure. 6: Confusion Matrix obtained using HGB Classifier for column Ticket Priority.

Figure 6 illustrates the Receiver Operating Characteristic (ROC) curves and corresponding Area Under the Curve (AUC) values for the "Ticket Priority" classification task using the HGB classifier delivers outstanding ROC performance, with nearly perfect curves that hug the top-left corner of the plot (AUC = 1.00 for Critical, High, Low, and Medium, and micro-average AUC = 1.00). This near-ideal result indicates almost flawless discrimination between all ticket priority classes on the test set, confirming the proposed HGB model's exceptional effectiveness when trained on XLNet embeddings for this task.

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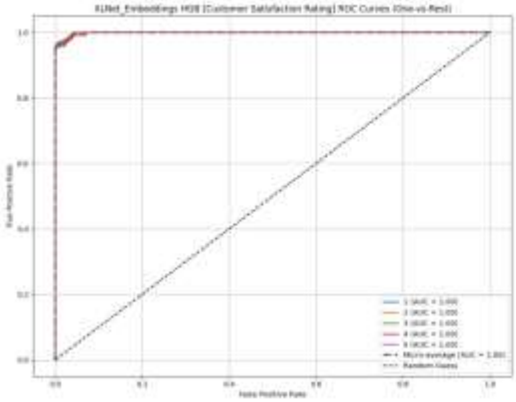

Figure. 7: Confusion Matrix obtained using HGB classifier for column customer Satisfaction.

Figure 7 presents the ROC curves and corresponding AUC values for the multi-class customer satisfaction rating prediction task (5 rating levels, from 1 to 5) using the HGB classifier delivers outstanding ROC performance, with nearly perfect curves that approach the ideal top-left corner (AUC = 1.00 for all individual classes 1 through 5, and micro-average AUC = 1.00). This near-ideal result demonstrates almost flawless discrimination across all customer satisfaction rating levels on the test set, confirming the proposed HGB model's exceptional effectiveness when trained on XLNet embeddings for this ordinal classification task.

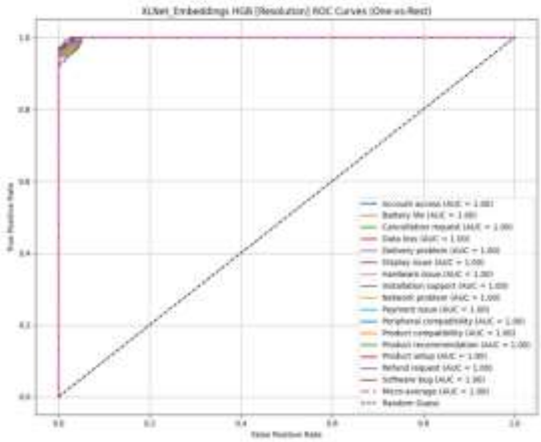

Figure. 8: Confusion Matrix obtained using HGB classifier for column resolution.

Figure 8 displays the ROC curves and corresponding AUC values for the multi-class "Resolution" prediction task using the HGB classifier exhibits outstanding ROC performance, with nearly perfect curves that hug the top-left corner of the plot for every resolution category (AUC = 1.00 across all classes, micro-average AUC = 1.00). This ideal result demonstrates flawless discrimination between all resolution types on the test set, confirming the proposed HGB model's exceptional effectiveness and clear superiority when trained on XLNet embeddings for the resolution prediction task.

Table 1: Overall Performance Comparison of Classification models for column “Ticket Priority”.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)

QDA	27.24	27.58	28.27	22.59
NC	27.24	27.58	28.27	22.59
SGD	52.77	58.10	51.92	51.02
LDA	57.63	57.46	57.47	57.45
HGB	96.17	96.23	96.11	96.16

Table 1 shows the overall performance comparison of different classification models for predicting Ticket Priority using XLNet embeddings. The HGB model achieves the highest performance with an accuracy of 96.17%, along with similarly high precision, recall, and F-score, indicating highly reliable predictions. Linear models such as LDA and SGD Classifier deliver moderate performance, while QDA and NC perform poorly, with only about 27% accuracy. This highlights the superiority of ensemble tree-based methods over simpler classifiers for accurate ticket priority prediction.

Table 2 presents the overall performance comparison of various classification models for predicting Customer Satisfaction using XLNet embeddings. Among all models, HGB clearly outperforms the others, achieving the highest accuracy of 96.26% along with similarly high precision, recall, and F-score values, indicating robust and reliable predictions. Linear models like LDA and SGD Classifier show moderate performance, with accuracies around 50–56%, while QDA and NC perform poorly, achieving only about 23% accuracy. This demonstrates the effectiveness of ensemble tree-based methods over simpler classifiers for multi-class customer satisfaction prediction.

Table 2: Overall Performance Comparison of Classification models for column “Customer Satisfaction”.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
QDA	23.41	20.69	22.90	19.02
NC	23.41	20.64	22.90	19.02
SGD	49.75	54.93	49.36	48.97
LDA	56.01	56.03	55.98	56.00
HGB	96.26	96.28	96.27	96.27

Table 3 presents the performance comparison of classification models for predicting Resolution using XLNet embeddings. The HGB model again outperforms all others, achieving the highest accuracy of 95.41% along with strong precision, recall, and F-score, indicating highly reliable predictions. LDA and SGD Classifier show moderate performance, while simpler models like QDA and NC perform very poorly, with accuracies below 8%. This demonstrates the effectiveness of ensemble tree-based models for complex multi-class resolution prediction in support tickets.

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Table 3: Overall Performance Comparison of classification models for column resolution.

Model	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
QDA	2.84	0.63	2.57	1.00
NC	7.83	11.44	7.71	5.10
SGD	50.47	69.22	49.83	44.78
LDA	63.17	63.50	63.32	63.16
HGB	95.41	95.60	95.40	95.48

Figure 9 illustrates the GUI-based implementation of the proposed hybrid machine learning system for support ticket analysis. The left panel shows various workflow buttons including Dataset Upload, Preprocessing, EDA, XLNet Feature Extraction, Classifier Training (QDA, LDA, SGD, NC, HGB), Prediction, and Comparison Tables. The right panel displays real-time ticket entries with predicted values for Ticket Priority, Customer Satisfaction Rating, and Resolution. This interface demonstrates how raw support ticket data is transformed through NLP preprocessing, feature extraction, and classification to produce actionable insights for customer service management.

Figure. 9: Real time predictions of customer satisfaction in support tickets.

5. Conclusion

The research successfully demonstrates an intelligent, automated solution for predicting multiple critical attributes of customer support tickets like priority, satisfaction rating, and resolution by combining the deep contextual language understanding capability of XLNet embeddings with the efficient and robust classical machine learning techniques, particularly the HGB classifier. This hybrid approach effectively leverages the strengths of both transformer-based feature extraction and classical algorithms, resulting in high prediction accuracy and operational scalability. It significantly reduces manual intervention, accelerates ticket triage processes, and enhances overall customer service quality. The exploratory analyses and visualization components provide valuable insights into

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ticket data characteristics, further supporting continuous improvement in customer support workflows.

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