Customer Support Ticket Categorization and Prioritization Using Natural Language Processing

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Abstract: Efficient and effective customer service relies heavily on the systematic management of customer support tickets. This paper presents an Natural Language Processing (NLP) - driven system designed to automate the categorization and prioritization of customer support tickets, significantly enhancing service efficiency. The system analyzes ticket content using machine learning models and deep learning models for both categorization and prioritization tasks. Categorization is achieved using Topic Modeling (NMF) to identify department-specific categories, while ticket priority levels are determined by extracting urgency and impact keywords. By leveraging these techniques, the system streamlines ticket handling, reduces manual intervention, and optimizes resource allocation. Experimental results demonstrate high accuracy, scalability, and improved operational efficiency, ultimately enhancing customer satisfaction.

1 INTRODUCTION

In today's highly competitive market, customer support is the order of the day for customer satisfaction and loyalty. Support teams face the ongoing challenge of managing a high volume of diverse queries, such as payment issues, general inquiries, technical problems, and product requests. Accurate categorization and prioritization are crucial to ensure swift, personalized resolutions that meet customer expectations. Traditional ticket handling processes rely heavily on manual efforts, which are time-consuming, labor-intensive, and prone to human error. As customer bases expand, the need for intelligent, automated solutions to streamline these operations becomes increasingly evident. Efficient categorization and prioritization are, therefore, critical components of modern customer support systems.

This study introduces an advanced framework leveraging machine learning and deep learning techniques to address these challenges effectively. The framework classifies support tickets into appropriate departmental categories and assigns priority levels based on factors like urgency and impact. Using a comprehensive dataset of 78,313 customer complaints, the work rigorously builds and evaluates various ML and DL models for these tasks. To handle unlabeled data, Topic Modeling techniques such as Non-negative Matrix Factorization (NMF) are applied to categorize queries into five distinct departmental groups. By automating support ticket management, this framework aims to significantly enhance operational efficiency, reduce manual effort, and improve overall customer satisfaction. This automation ultimately strengthens customer relationships and fosters long-term loyalty by providing timely, accurate support.

2 LITERATURE SURVEY

In 2024, Carla Vairetti et al. (Vairetti, Aránguiz, et al. , 2024) introduced a framework that combines multicriteria decision-making (MCDM) and deep learning to prioritize complaints. The framework automates complaint classification and prioritization using text analytics and operational research techniques. It bridges deep learning with traditional machine learning by incorporating pretrained models. MCDM is applied to combine multiple criteria into a single prioritization score, enhancing decision-

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making. The framework's effectiveness is demonstrated by its application to real-world data from a Chilean agency. This approach improves efficiency in managing complaints across various service sectors.

In 2022, Alvaro Aldunate et al. (Aldunate, Maldonado, Declerck, 2022)presented a methodology which utilizes BERT and transfer learning to uncover customer satisfaction factors across various sectors. It highlights the superiority of deep learning models over traditional text mining methods in classification accuracy. The research emphasizes the importance of automated evaluation of consumer feedback for decision-making in the service sector. A four-step methodology is used to extract relevant insights from open-ended survey responses. The study demonstrates how NLP and deep learning can enhance customer experience analysis.

In 2023, Peter Adebowale Olujimi et al. (Olujimi, and, Ibijola, 2023)] reviewed 73 studies on the use of NLP to automate customer queries across various industries. The research highlights benefits like faster response times, improved accuracy, and higher customer satisfaction, indicating the increasing demand for automated customer care systems. It suggests that future research could explore advanced NLP models and AI integration to further enhance consumer interactions. The study emphasizes the importance of thorough literature reviews for credibility and adds to the growing body of knowledge on NLP's role in transforming customer service and boosting corporate performance.

In 2021, H. A. Ahmed et al. (Ahmed, Bawany, et al. , 2021) introduced CaPBug, a system for automating software bug prioritization and learning models, including CNNs, BiLSTMs, and BERT. It demonstrated that BERT combined with TF-IDF and Logistic Regression achieved the best macro-averaged F1-score, highlighting the effectiveness of pre-trained models in automating complaint prioritization and improving resource allocation in customer service.

The system analyzes bug reports from Eclipse and Mozilla using supervised machine learning and natural language processing (NLP). Bug reports were manually classified into six categories and five priority levels from 2016 to 2019. The system predicts bug categories and priorities using textual and categorical data, with feature extraction using TF-IDF and NLP algorithms. Popular classification methods are employed. The system improves software maintenance by accurately predicting issues and addressing class imbalance in priority levels.

In 2020, Nikhil Patel et al. (Patel, and, Trivedi, 2020) explored the use of predictive modeling, machine learning, NLP, and AI chatbots to enhance customer support and loyalty. The study examines NLP applications across industries like marketing, e-commerce, healthcare, telecommunications, and finance, based on 26 articles from 2015 to 2022. Common techniques like TF-IDF and SVM are highlighted. The research discusses the need for larger datasets to improve NLP applications in customer service. Various models like TextCNN, AdaBoost, and LDA were also applied in the study, focusing on response quality, helpfulness, and appropriateness.

In 2018, Sridhar Ramaswamy et al. (Ramaswamy, and, DeClerck, 2020)explored using NLP and deep learning for customer perception analysis. The study integrates various technologies to extract insights from consumer feedback, emphasizing the importance of understanding consumer attitudes and preferences. It discusses methods like named entity recognition, rule-based semantics, and semantic annotation to improve perception analysis. The authors suggest using industry-specific survey questions for more detailed insights.

In 2018, Ruanda Qamili et al. (Qamili, Shabani, et al. , 2018) aimed to enhance customer service productivity by incorporating machine learning into ticketing systems. The study covers sentiment analysis, ticket assignment, and spam detection in customer support. It proposes an automated solution to improve ticket management and reduce false positives in spam filtering using a conservative unanimity method. The authors emphasize the importance of addressing delayed issue resolutions in customer service.

In 2021, Nokudaiyaval G et al. (Kirthiga, and, Ghayathri, 2021)developed a system using NLP and the BERT algorithm to reduce labor and save customers' time in customer support. NLP is used for speech recognition, while BERT handles text classification and prediction. Unlike existing systems using IVR to route calls, the proposed solution generates automated responses without human intervention. The system is pre-trained using a closed dataset, with tokenization applied to customer input. BERT's bidirectional search locates key interaction information, providing a response between start and finish parameters. This approach improves customer support services by reducing reliance on human interactions.

In 2022, Blümel and Zaki (Blümel, and, Zaki, 2022) conducted a comparative analysis of classical and deep learning-based natural language processing methods to prioritize customer complaints. The study combined feature engineering techniques like TF-IDF and Word2Vec with machine learning classifiers and deep learning models, including CNNs, BiLSTMs, and BERT. It demonstrated that BERT combined with TF-IDF and Logistic Regression achieved the best macro-averaged F1-score, highlighting the effectiveness of pre-trained models in automating complaint prioritization and improving resource allocation in customer service.

In 2018, Silva et al. (Silva, Pereira, et al. , 2018) introduced a machine learning-based module to automate the categorization of IT incident tickets. The proposed system uses a support vector machine (SVM) to classify tickets, achieving an accuracy of approximately 89% on real-world data. The module enhances incident management productivity by reducing routing errors and minimizing delays in ticket assignment, contributing to improved IT service delivery and customer satisfaction.

In 2023, Reddy and Prabhu (Reddy, and, Prabhu, 2023) conducted a comprehensive review on the role of artificial intelligence in request management processes. The study highlights AI's transformative potential in automating request capture, logging, categorization, and prioritization using techniques like NLP, machine learning, and chatbots. It discusses the challenges in manual request management and the benefits of AI in enhancing workflow optimization, resource allocation, and scheduling. The paper underscores the impact of AI in improving efficiency, accuracy, and customer satisfaction in request management systems.

In 2019, Lucini et al. (Lucini, Tonetto, et al. , 2019) proposed a text mining framework to analyze airline customer satisfaction using Online Customer Reviews (OCRs). They examined 55,775 reviews across 419 airlines, identifying 27 satisfaction dimensions and 882 adjectives through Latent Dirichlet Allocation (LDA). The framework achieved a prediction accuracy of 79.95% for customer airline recommendations. Key satisfaction factors included cabin staff, onboard service, and value for money. The study provides actionable insights, highlighting the need for tailored strategies in customer service and comfort based on cabin class preferences to enhance competitiveness in the airline industry.

In 2022, Ishizuka et al. (Ishizuka, Washizaki, et al. , 2022) proposed a novel method to improve feature comprehension in software development projects using issue tickets. The method categorizes tickets through clustering and visualizes them using heatmapping and principal component analysis (PCA). It also includes ticket lifetime visualization for time-series analysis and keyword relationships among ticket categories. A case study on an industrial project demonstrated its effectiveness in helping project members and newcomers understand implemented features. The study emphasizes the value of structured, visualized tickets in enhancing onboarding and comprehension of multi-dimensional requirements in evolving projects.

In 2019, Al-Hawari and Barham (Hawari, and, Barham, 2019) introduced a machine learning-based help desk system aimed at improving IT service management. The system utilizes a ticket classification model to streamline ticket resolution by automatically associating help desk tickets with the correct service. The methodology involves training ticket data, preprocessing, stemming, feature vectorization, and algorithm tuning. Experimental results revealed that incorporating ticket comments and descriptions significantly improved model accuracy from 53.8% to 81.4%. The system also features administrator and user views, supports automatic email notifications, and enables performance measurement through key performance indicators (KPIs) for IT staff and processes.

In 2023, Benitez Pereira et al. (Pereira, Pizzio, et al. , 2023) presented a machine learning model for classifying IT support tickets to enhance help desk operations. The model categorizes incoming support tickets into seven topics with an average precision of 75%. To support daily operations, a web prototype was developed, offering both frontend and backend functionalities for IT analysts. The code, model, and anonymized data were made publicly available for replication of the study. This approach helps minimize ticket resolution time and improves user satisfaction by automating ticket topic identification.

3 PROPOSED METHODOLOGY

3.1 Data Collection

The dataset comprises complaint texts submitted by customers to a financial institution. This dataset, sourced from Kaggle, is specifically designed to facilitate the classification and prioritization of customer support tickets. It contains a total of 78,313 individual complaints, each in JSON format, capturing various issues and grievances reported by users. The data aims to support the development of models or systems that can categorize these complaints effectively and determine their priority levels, enhancing customer service workflows.

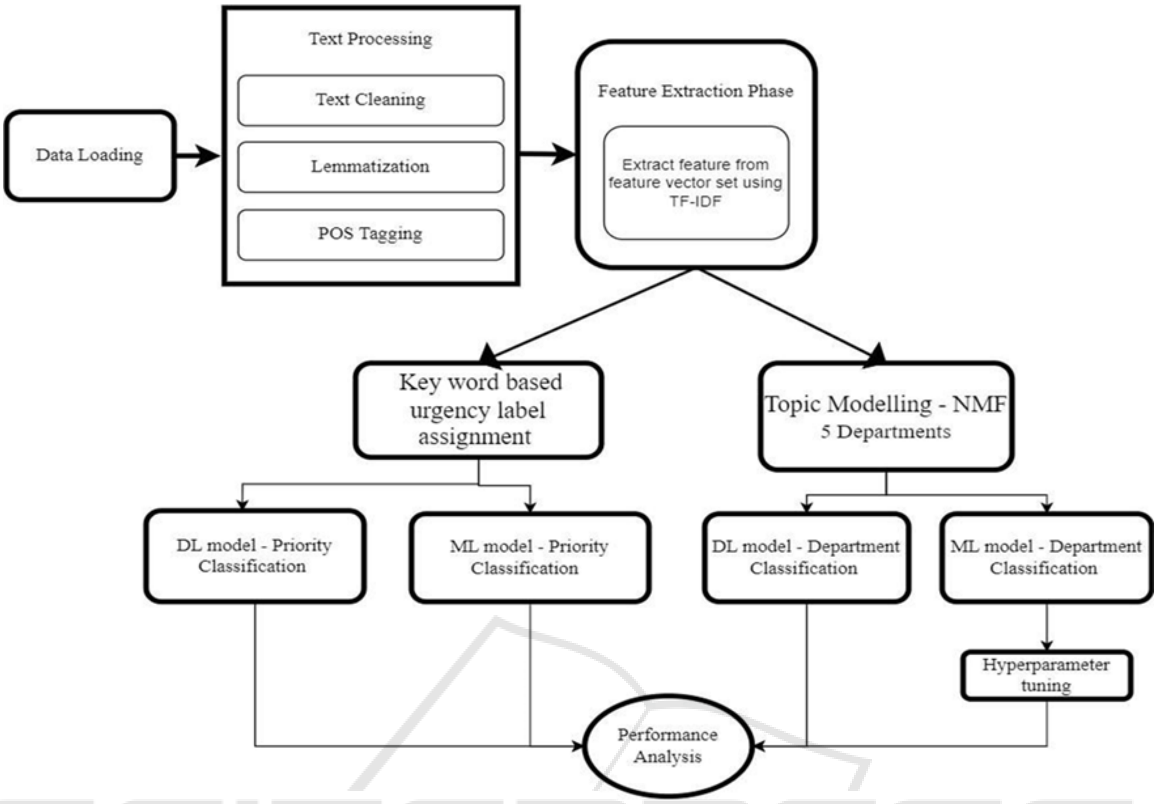

Figure 1: Department classification ML model's accuracies.

3.2 Data Preprocessing

The initial phase of classifying customer complaints into departments involves comprehensive text preprocessing to ensure data quality and relevance. This process begins by removing unnecessary or duplicate fields from the dataset, retaining only essential information for analysis. Blank or incomplete entries are identified and eliminated to maintain data integrity. Text data is standardized through methods like converting all text to lowercase and removing punctuation using regular expressions, which simplifies further analysis. Lemmatization is applied to reduce words to their root forms, enhancing consistency and aiding tasks such as information retrieval and sentiment analysis. Masked personal data is removed to eliminate personal details of the user.

Feature extraction is initially performed using TF-IDF (Term Frequency-Inverse Document Frequency), a technique that highlights the most important and relevant terms within the complaints. By analyzing the frequency of terms across multiple documents, it helps identify key words that are significant in the context of the dataset. These extracted features are then used for topic modeling, where the most common terms present across the complaints are analyzed to uncover underlying, latent themes within the text data. Topic modeling is carried out using NMF (Non-negative Matrix Factorization). For each topic, the top 10 words are extracted, and these words are manually mapped to predefined categories such as Retail Banking Operations, Credit Card Management, Payment and Billing, Dispute Reporting, and Mortgages/Loans. This mapping process ensures that each customer complaint is accurately classified into the appropriate department, which facilitates better message forwarding and streamlined management of the complaints. For prioritization of complaints, urgency is determined by matching text tokens against a predefined list of urgent words that signify a time-sensitive issue. Advanced NLP tools, such as spaCy and negspacy, are used to detect negation within the text, ensuring that phrases like "not urgent" are correctly interpreted. This method guarantees that complaints are accurately classified as urgent or non-urgent, even when negation modifies the meaning of key words. This approach enhances the ability to prioritize critical issues effectively, ensuring that the most time-sensitive complaints are addressed promptly.

3.3 Machine Learning Models

3.3.1 Logistic Regression

This algorithm establishes a relationship between the input features and the probability of a binary outcome by applying a logistic function, making it highly effective for predicting outcomes in two categories. This algorithm is ideal for classifying customer complaints into predefined categories and prioritizing them. In this case, it helps to extract the most relevant terms from the complaints using TF-IDF, which boosts the model's ability to accurately categorize and prioritize complaints. The model achieved a classification accuracy of 91.99%, efficiently sorting complaints into their respective categories. For prioritization, the model achieved an accuracy of 90.11%, demonstrating its ability to accurately determine the urgency of complaints.

3.3.2 Decision Tree

The Decision Tree is a algorithm which divides the dataset into smaller subsets by selecting decision nodes based on the most relevant features, forming a tree structure where each leaf represents a classification label or a continuous value. This method is effective for handling complex datasets with multiple features, and it is highly interpretable. By creating decision boundaries based on feature values, it excels at categorizing complaints and prioritizing them according to urgency. The model achieved a classification accuracy of 78.44%, accurately sorting complaints into predefined categories. For prioritization, it achieved an exceptional accuracy of 99.96%, effectively differentiating between urgent and non-urgent complaints with high precision.

3.3.3 Random Forest Classifier

This generates a collection of decision trees, each built from various subsets of the data, and then averages their outputs to mitigate overfitting and improve accuracy. This method is particularly effective for handling complex datasets, managing large volumes of data, and providing feature importance metrics. By using an ensemble approach, Random Forest reduces both bias and variance compared to a single decision tree, making it a reliable choice for classifying and prioritizing complaints. The model achieved a classification accuracy of 81.13%, successfully organizing complaints into predefined categories. For prioritization, it reached an accuracy of 90.03%, effectively distinguishing between urgent and non-urgent complaints.

3.3.4 Support Vector Machine

Support Vector Machine (SVM) identifies the optimal hyperplane that separates data points into distinct classes, maximizing the margin between the nearest points of different categories. This makes SVM particularly effective for handling high-dimensional datasets and complex classification problems. Additionally, it excels in scenarios where the data is not linearly separable, a common characteristic of real-world datasets. In this study, SVM achieved an impressive classification accuracy of 91.51%, effectively sorting customer complaints into predefined categories. For prioritization, the model demonstrated a strong performance with an accuracy of 94.68%, efficiently distinguishing between urgent and non-urgent complaints.

3.3.5 Multinomial Naïve Bayes

Multinomial Naive Bayes is a algorithm tailored for text classification tasks. It leverages Bayes' Theorem and operates under the assumption that features, such as words in a text dataset, are conditionally independent of each other when conditioned on the class label. This algorithm is ideal for classifying customer complaints into predefined categories and prioritizing them, as it can handle large vocabularies and text-based features efficiently. Its probabilistic nature helps in assigning the most likely category based on the frequency of words in the complaints. The model achieved an accuracy of 71.87% for classification, accurately categorizing customer complaints into predefined categories. For prioritization, the model achieved an accuracy of 89.39%, although it performed poorly on the "urgent" category, as reflected in its recall of 0%.

3.3.6 Gradient Boosting Machines

Gradient Boosting Machines (GBM) is an ensemble algorithm that integrates multiple weak models to form a robust predictive system, making it well-suited for complex tasks such as text classification. It has proven effective in categorizing customer complaints and ranking them by urgency. GBM excels at processing large datasets and modeling intricate patterns, making it a strong candidate for prioritizing and classifying customer issues. The model demonstrated high performance, achieving a classification accuracy of 90.45% and a prioritization accuracy of 98.84%, particularly excelling in identifying "urgent" and "not urgent" complaints.

3.3.7 XG Boosting

XG Boost is an advanced gradient boosting algorithm known for its speed and performance in classification tasks, making it well-suited for customer complaint classification and prioritization. By leveraging decision trees in an ensemble framework, XG Boost efficiently handles large datasets with missing values and complex relationships. In the classification task, the model achieved an accuracy of 91.17% in categorizing complaints, while for prioritization, it achieved an outstanding 99.73% accuracy, excelling at distinguishing between "urgent" and "not urgent" complaints. Its high precision and recall reflect its strong predictive performance.

3.4 Deep Learning Models

3.4.1 BERT

BERT (Bidirectional Encoder Representations from Transformers), is an advanced transformer leveraged deep learning model developed for natural language understanding. By employing a bidirectional attention mechanism, it analyzes a word's context by considering the words on both sides within a sentence, making it exceptionally efficient for tasks like text classification. This makes BERT particularly suitable for tasks like department categorization and urgency prioritization, where understanding the nuanced meaning of words in context is crucial. For department categorization, BERT achieved an accuracy of 81%, while for urgency prioritization, it performed even better with an accuracy of 92%, showcasing its strong capability in both tasks.

3.4.2 RNN

A Recurrent Neural Network (RNN) is a model tailored for sequential data processing, using a hidden state to retain information from prior inputs and capture dependencies over time. This makes RNNs especially suitable for tasks involving sequences, such as text classification in department categorization and urgency prioritization, where the order of words or phrases can influence the meaning. In the department categorization task, RNN achieved an accuracy of 80%, while for urgency prioritization, it also achieved an accuracy of 92%, showing that it can handle both tasks effectively.

3.4.3 CNN

A Convolutional Neural Network (CNN) is typically used for image processing but has proven effective for text classification tasks by applying convolutional layers to extract local patterns from sequences of text. This ability to detect local features makes CNNs suitable for department categorization and urgency prioritization, where the focus is on identifying important keywords or phrases within text. CNNs are particularly effective when the task benefits from recognizing local patterns and structures in data, such as words or phrases with specific relevance. In department categorization, CNN achieved an accuracy of 80%, while for urgency prioritization, the model achieved an accuracy of 91%, showing its ability to handle both tasks with competitive performance.

4 PERFORMANCE ANALYSIS

This study evaluates model performance using Precision, Recall, F1-Score, and Accuracy. Precision indicates the ratio of correctly predicted positive cases to the total positive predictions, showcasing the model's reliability in positive classifications. Recall, assesses the model's effectiveness in detecting all actual positive instances, calculated as the proportion of true positives among all actual positives. The F1-Score, offers a balanced evaluation by accounting for both false positives and false negatives, making it particularly valuable for imbalanced datasets. Lastly, Accuracy measures the percentage of all correct predictions, encompassing both true positives and true negatives, providing a comprehensive performance overview.

Table 1: Comparison of ml models for department categorization

Model	Precision	Recall	F1 Score	Accuracy (%)
Logistic Regression	0.93	0.91	0.92	0.92
SVM	0.92	0.91	0.91	0.92
XG Boost	0.91	0.91	0.91	0.91
Gradient Boosting Machines	0.90	0.90	0.90	0.90
Random Forest	0.83	0.77	0.78	0.81
Decision Tree	0.78	0.78	0.78	0.78
Multinomial Naïve Bayes	0.79	0.64	0.61	0.72

Table 2: Comparison of dl models for department categorization

Model	Accuracy(%)
BERT	0.81
RNN	0.80
CNN	0.80

Table 3: Comparison of dl models for urgency prioritization

Model	Accuracy(%)
BERT	0.92
RNN	0.92
CNN	0.91

Table 4: Comparison of ml models for urgency prioritization

Model	Precision	Recall	F1 Score	Accuracy (%)
Decision Tree	1.00	1.00	1.00	1.00
XG Boost	1.00	1.00	1.00	1.00
Gradient Boosting Machines	0.99	0.95	0.97	0.99
SVM	0.97	0.75	0.82	0.95
Random Forest	0.94	0.53	0.53	0.90
Logistic Regression	0.93	0.53	0.54	0.90
Multinomial Naïve Bayes	0.45	0.50	0.47	0.89

5 RESULTS AND DISCUSSION

To find best model for both the categorization of departmental affiliations and the prioritization of tickets, the study conducted a thorough evaluation of the performance of various machine learning and deep learning architectures. In the department classification task, logistic regression emerged as the best-performing machine learning model, achieving the highest accuracy of 91.99%, closely followed by SVM (91.51%) and XG Boost (91.17%). Gradient Boosting Machines demonstrated solid results with an accuracy of 90.45%, while Random Forest and Decision Tree performed moderately, achieving 81.13% and 78.44%, respectively. Multinomial Naive Bayes, however, recorded the lowest accuracy at 71.87%, indicating its limited suitability for this task. Among the deep learning models, BERT stood out with the highest accuracy of 81.00%, showcasing its ability to leverage pre-trained contextual embeddings effectively. CNN and RNN followed closely with accuracies of 80.83% and 80.45%, respectively, indicating competitive but slightly lower performance compared to transformer-based architectures. In the priority classification task, Decision Tree outperformed all other models, achieving a remarkable accuracy of 99.96%. Gradient Boosting Machines (98.84%) and XG Boost (99.73%) also demonstrated exceptional performance. Logistic Regression (90.11%), Random Forest (90.03%), and SVM (94.68%) showed consistent and reliable results, while Multinomial Naive Bayes lagged slightly with an accuracy of 89.39%. Among deep learning models, BERT again proved to be the most effective, achieving an accuracy of 92.64%, followed closely by CNN (92.50%) and RNN (91.79%). These results reaffirm the effectiveness of BERT's pre-trained embeddings in handling natural language tasks with contextual complexity.

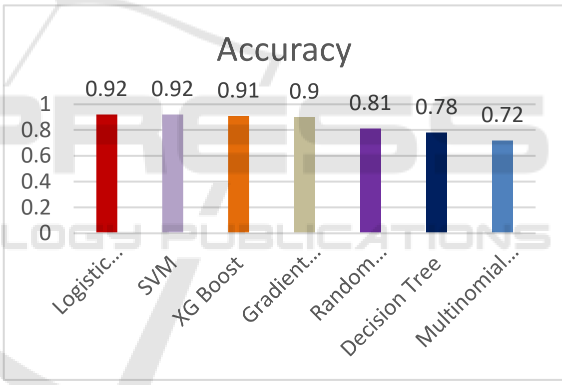

Figure 2: Department classification ML model's accuracies

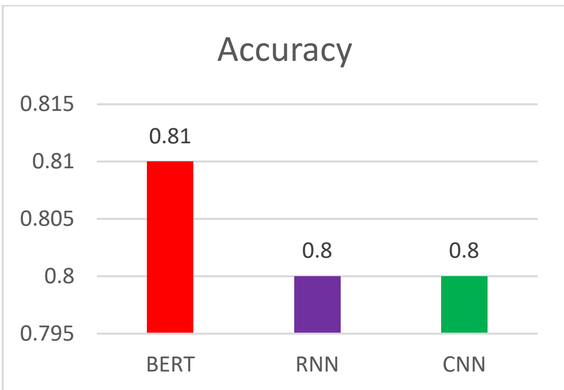

Figure 3: Department classification DL model's accuracies

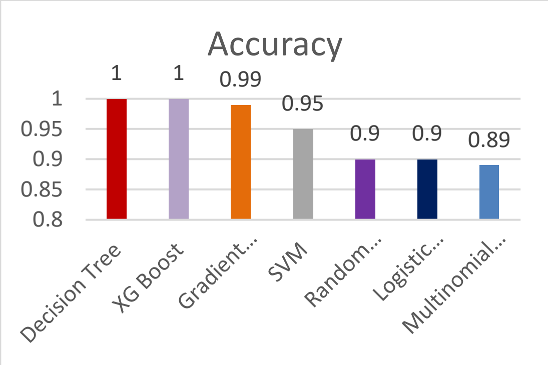

Figure 4: Priority classification ML model's accuracies

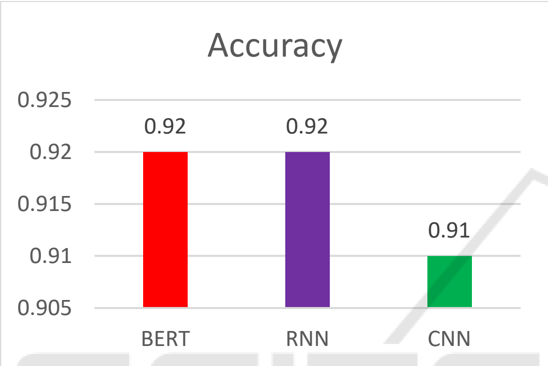

Figure 5: Priority classification DL model's accuracies

6 CONCLUSIONS

This project represents a significant stride in automating customer support ticket management, offering a comprehensive solution for both department categorization and priority classification. Logistic regression emerged as a standout performer in department classification, achieving an impressive accuracy of 91.99%, closely trailed by SVM and XG Boost. Conversely, decision tree excelled in priority classification, boasting an exceptional accuracy of 99.96%. The inclusion of deep learning models, notably BERT, showcased competitive performance, particularly in priority classification, achieving an accuracy of 92.64%. These findings highlight the efficacy of machine learning (ML) and deep learning (DL) techniques in enhancing ticket management processes and elevating customer satisfaction levels. Deep learning models, like BERT, will exhibit superior performance when confronted with larger datasets and complex, unstructured data, as they can discern intricate patterns and dependencies. Furthermore, DL models may outperform ML models when trained over numerous epochs, leveraging their ability to learn hierarchical representations of data. Our study extends beyond conventional approaches by incorporating innovative topic modelling techniques to label unlabelled data effectively. This approach not only improves model accuracy but also demonstrates versatility and practicality in real-world support environments, addressing the challenge of limited availability of labelled data when coming to a real world problem. By integrating both department categorization and priority classification into a unified framework, our research achieves remarkable accuracy levels, surpassing previous studies that focused solely on one aspect. Moving forward, future research endeavours may explore additional optimization strategies and investigate the deployment of these models in diverse support environments to validate scalability, effectiveness, and real-world applicability

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