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Streamlining Multilingual Service Desk Operations: A Machine Learning Approach to Classification and Time Prediction

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ABSTRACT

This study addresses the complex challenge of managing multilin- gual service desk (SD) tickets, which span across 35 categories and 150 sub-categories. To streamline this process, we developed two sophisticated classification models. The first model automatically predicts the primary category of a ticket based on its summary and description, leveraging advanced natural language processing (NLP) techniques. The second model refines this by predicting the sub- category within the identified primary category. In addition, we im- plemented a robust regression model to accurately estimate the time required to resolve each ticket, based on its content. Furthermore, a solution recommendation model was developed to suggest relevant solutions from historical data, enhancing the efficiency of the service desk operations. By integrating these models, our approach signifi- cantly improves the accuracy and speed of ticket categorization and resolution. This leads to timely resolutions, reduced downtime, and enhanced user satisfaction. Through these models, we aim to stream- line SD processes, reduce resolution times, and provide actionable insights that contribute to improved service quality and operational efficiency.

Key words: natural language processing (NLP), Streamlining Multilingual Service Desk Operations, Machine Learning Approach, Time Prediction

1. INTRODUCTION

Service desks are essential components in modern organizations, tasked with managing a variety of technical and operational issues. These issues can range from simple password resets to complex network problems, and they require timely resolution to maintain business continuity. The complexity increases significantly in mul- tilingual environments where service desk tickets are submitted in different languages and must be categorized accurately across nu- merous categories and sub-categories.

In recent years, advancements in machine learning have opened new avenues for automating and enhancing service desk operations. This study focuses on developing a robust system to handle multilin- gual service desk (SD) tickets, classified into 35 categories and 150 sub-categories. The primary objective is to improve efficiency and ac- curacy in categorizing and resolving tickets through the application of machine learning models.

The first challenge addressed is the accurate classification of SD tickets into predefined categories and sub-categories. Manual cate- gorization, though effective, is not scalable given the volume and variety of tickets in large organizations. Therefore, two classification models were developed. The first model predicts the main category of a ticket based on its summary and description, utilizing natural language processing (NLP) techniques. The second model refines this classification by predicting the sub-category within the identi- fied main category. This dual-model approach ensures that tickets are accurately categorized, facilitating faster and more effective resolution.

Another critical aspect of service desk management is predicting the time required to resolve each ticket. Accurate time prediction helps in resource allocation and setting user expectations. To this end, we developed a regression model that estimates the resolution time based on the ticket's summary and description. By analyzing histori- cal data, the model provides time estimates that help in planning and prioritizing service desk activities.

In addition to classification and time prediction, providing solu- tions based on past resolved tickets can significantly speed up the resolution process. A solution recommendation model was created to suggest relevant solutions based on the content of new tickets. This model uses similarity measures to match new tickets with past resolved ones, offering potential solutions that have been effective in similar situations.

Rest of the paper is organised as follows

Section 2 presents the background of service desk operations, the importance of accurate ticket classification, and the chal- lenges in multilingual environments.

Section 3 reviews related work on service desk issue analysis, machine learning classification models, regression for time prediction, and solution recommendation systems.

Section 4 details our methodology, including data collection, preprocessing, and the development of the classification, re- gression, and solution recommendation models.
Section 5 presents the results, including the performance metrics of the classification and regression models, and the accuracy of the solution recommendations.
Section 6 provides our conclusion, summarizing key findings and proposing future work to enhance service desk operations using advanced machine learning techniques.

2.BACKGROUND

Service desks are critical components of modern organizations, pro- viding a centralized point of contact for resolving a wide range of technical and operational issues. These desks support various functions from handling IT-related incidents to assisting with ad- ministrative tasks. Effective service desk management is crucial for maintaining business continuity and ensuring user satisfaction. This section delves into the fundamental aspects of service desk opera- tions, the challenges posed by multilingual environments, and the importance of accurate ticket classification and timely resolution.

A. Importance of Service Desk Operations

Service desks play a pivotal role in addressing issues that can impact business operations. They are responsible for ensuring that incidents are resolved promptly and efficiently, minimizing downtime and disruption. Effective service desk management contributes to:

- [1]. Operational Efficiency: - By resolving issues quickly, ser- vice desks help maintain the smooth operation of business processes.
- [2]. User Satisfaction: - Timely and accurate issue resolution enhances user confidence and satisfaction, leading to a better overall experience.
- [3]. Resource Optimization: - Efficient service desk operations enable better allocation and utilization of resources, reducing waste and improving productivity.

B. Challenges in Multilingual Environments

The complexity of service desk operations increases significantly in multilingual environments. Organizations operating in global markets often receive service desk tickets in various languages, each requiring accurate interpretation and categorization. The key challenges include:

- [1]. Language Barriers: Service desk agents must understand and accurately interpret tickets submitted in different lan- guages, which can be difficult without the appropriate lan- guage skills or tools.
- [2]. Inconsistent Terminology: Ifferent languages and regions may use varied terminology to describe similar issues, com- plicating the classification process.
- [3]. Cultural Differences: Cultural nuances and differences in communication styles can affect how issues are reported and understood.

These challenges necessitate the development of robust systems ca- pable of handling multilingual data effectively, ensuring that tickets are accurately categorized and resolved regardless of the language in which they are submitted.

C. Importance of Accurate Ticket Classification

Accurate classification of service desk tickets is essential for several reasons:

- [1]. Efficient Routing: Correctly classified tickets can be routed to the appropriate teams or individuals for resolution, reduc- ing delays.
- [2]. Prioritization: Classification helps in prioritizing tickets based on their severity and impact, ensuring that critical issues are addressed first.
- [3]. Data Analysis: Accurate classification enables meaningful analysis of service desk data, identifying trends and recurring issues that can inform decision-making and process improve- ments.

Manual classification, while effective, is labor-intensive and not scalable. Automated classification models using machine learning techniques offer a scalable solution that can handle large volumes of tickets with high accuracy.

D. Regression Models for Time Prediction

Predicting the time required to resolve service desk tickets is a criti- cal aspect of service desk management. Accurate time predictions
help in:

- [1]. Resource Planning: By estimating the time needed to resolve issues, managers can allocate resources more effectively.
- [2]. Setting Expectations: Providing users with realistic time- frames for issue resolution helps manage expectations and improves satisfaction.
- [3]. Performance Monitoring: Time predictions enable the mon- itoring of service desk performance, identifying areas for im- provement and ensuring that service level agreements (SLAs) are met.

Regression models trained on historical ticket data can provide re- liable time estimates, taking into account various factors such as ticket complexity and past resolution times.

E. Solution Recommendation Systems

Providing relevant solutions based on past resolved tickets can sig- nificantly expedite the resolution process. Solution recommendation systems use historical data to:

[1]. Suggest Solutions: By matching new tickets with similar past issues, these systems can suggest relevant solutions, reducing the time agents spend searching for answers.
[2]. Improve Consistency: Recommendations based on histor- ical data ensure that solutions are consistent and effective, improving the overall quality of service.
[3]. Enhance Efficiency: Quick access to relevant solutions helps service desk agents resolve issues faster, enhancing opera- tional efficiency.

Implementing these models requires a comprehensive approach to data collection, preprocessing, and analysis, ensuring that the sys- tems are trained on high-quality data and can provide accurate and reliable recommendations.

F. Benefits of Integrating Machine Learning in Service Desk Operations

The integration of machine learning models in service desk opera- tions offers numerous benefits:

[1]. Scalability: Machine learning models can handle large vol- umes of data, making them suitable for organizations with extensive service desk operations.
[2]. Accuracy: Advanced algorithms and techniques ensure high accuracy in ticket classification, time prediction, and solution recommendation.
[3]. Efficiency: Automated processes reduce the manual effort required, freeing up service desk agents to focus on more complex issues.
[4]. Data-Driven Insights: Machine learning models can analyze large datasets to identify trends and patterns, providing valu- able insights that can inform decision-making and strategic planning.

In summary, the integration of machine learning in service desk operations addresses the challenges of multilingual environments, improves accuracy and efficiency, and provides actionable insights that enhance service quality and user satisfaction. This background sets the stage for the detailed methodology and results sections that follow, demonstrating the practical application and benefits of our approach.

3. RELATED WORK

The field of service desk management has seen significant advance- ments in recent years, particularly with the application of machine learning techniques to automate and enhance various aspects of ser- vice desk operations. This section reviews existing literature and tools related to service desk issue analysis, classification models, re- gression for time prediction, and solution recommendation systems.

A. Manual Categorization

Historically, service desk ticket classification has been performed manually by human experts. This process involves categorizing tick- ets based on their content, which requires a deep understanding of the issues and the terminology used in different contexts. While man- ual categorization can be accurate due to the nuanced understanding of human operators, it is inherently time-consuming and not scalable for large datasets. As organizations grow and the volume of service desk tickets increases, the limitations of manual categorization be- come evident. Inconsistent terminology, subjective interpretation, and human error further complicate the process, leading to delays and potential misclassifications.

B. Automated Classification

Automated classification using machine learning algorithms has emerged as a viable solution to the scalability and consistency issues of manual categorization. Techniques such as natural language pro- cessing (NLP) and text classification models have been employed to automatically categorize service desk tickets.

[1]. Natural Language Processing (NLP): NLP techniques are employed to process and analyze large amounts of natural lan- guage data. These techniques enable machines to understand the context and semantics of service desk tickets, allowing for more accurate classification. NLP methods include tok- enization, part-of-speech tagging, named entity recognition, and sentiment analysis, among others. These methods help in extracting meaningful features from the text, which can then be used for classification.
[2]. Text Classification Models: Various machine learning mod- els, such as Naive Bayes, Support Vector Machines (SVM), and neural networks, have been used for text classification. These models are trained on historical ticket data to learn patterns and predict categories for new tickets. For instance, a study by [Author et al., 2019] demonstrated the effectiveness of SVM and Naive Bayes in classifying IT service desk tickets with high accuracy. Similarly, [Author et al., 2018] explored the use of deep learning models, such as Convolutional Neu- ral Networks (CNN) and Recurrent Neural Networks (RNN), for categorizing customer support tickets, showing improved performance over traditional methods.

Automated classification not only reduces the time and effort re- quired for categorization but also improves consistency and accuracy. These models can continuously learn and adapt as they are exposed to more data, making them increasingly effective over time.

C. Regression Models for Time Prediction

Predicting the time required to resolve service desk tickets is another critical aspect of service desk management. Regression models are used to estimate the resolution time based on the ticket's summary and description.

[1]. Linear Regression: Linear regression models establish a re- lationship between the input features (e.g., ticket description, category) and the output variable (resolution time). These models are simple and interpretable but may not capture com- plex relationships in the data.

[2]. Advanced Regression Techniques: More advanced tech- niques, such as decision trees, random forests, and gradient boosting machines, have been employed to improve predic- tion accuracy. For example, [Author et al., 2017] used random forest regression to predict the resolution time for IT service requests, achieving better performance than linear regression models. Additionally, [Author et al., 2016] applied gradient boosting machines to predict ticket resolution times, high- lighting the model's ability to handle non-linear relationships and interactions between features.

[3]. Deep Learning Approaches: Recent studies have also ex- plored the use of deep learning for time prediction. [Author et al., 2018] implemented a Long Short-Term Memory (LSTM) network to predict the resolution time for customer service tickets, leveraging the model's capability to capture temporal dependencies and sequential patterns in the data.

D. Solution Recommendation Systems

Solution recommendation systems aim to suggest relevant solutions for new tickets based on historical data. These systems enhance the efficiency of service desk operations by providing agents with actionable insights and potential resolutions.

[1]. Similarity-Based Approaches: One common approach is to use similarity measures to match new tickets with previ- ously resolved ones. Techniques such as cosine similarity, Jaccard similarity, and Euclidean distance are used to identify similar tickets. [Author et al., 2015] demonstrated the use of cosine similarity to recommend solutions for IT support tickets, significantly reducing the time spent by agents on finding relevant solutions.

[2]. Case-Based Reasoning (CBR): CBR systems retrieve and adapt solutions from past cases to solve new problems. These systems store historical cases in a structured format, allowing for efficient retrieval and adaptation. [Author et al., 2014] applied CBR to service desk management, showing that the system could effectively recommend solutions by leveraging past experiences.

[3]. Machine Learning Models: Machine learning models, such as k-nearest neighbors (k-NN) and deep learning, have also been used for solution recommendation. [Author et al., 2019] implemented a k-NN model to recommend solutions based on the similarity between ticket descriptions, while [Author et al., 2020] used a deep learning approach to suggest solutions by learning complex patterns in the data.

E. Integration of Machine Learning in Service Desk Operations

The integration of machine learning models in service desk opera- tions offers numerous benefits, including scalability, accuracy, and efficiency. Automated classification and regression models stream- line the handling of large volumes of tickets, providing consistent and accurate categorization and time predictions. Solution recom- mendation systems further enhance efficiency by offering relevant solutions, reducing the time agents spend searching for resolutions. The combined use of these models creates a comprehensive frame- work for service desk management, addressing the challenges of multilingual environments and improving overall service quality. As machine learning techniques continue to evolve, their application in service desk operations will likely expand, offering even greater
benefits and capabilities.

In summary, the related work highlights the significant advance- ments in service desk management through the application of ma- chine learning techniques. These approaches address the limitations of manual categorization, improve the accuracy of time predictions, and provide effective solution recommendations, ultimately enhanc- ing the efficiency and effectiveness of service desk operations.

4. APPROACH

This section details the methodology used to develop the service desk issue analysis system, which includes data collection, preprocessing, and the implementation of classification, regression, and solution recommendation models.

A. Data Collection and Preprocessing

[1]. Data Collection: The first step in our approach was to collect a comprehensive dataset of service desk (SD) tickets. The data was aggregated from multiple business units within the organization, covering a diverse range of issues reported in various languages. Each ticket in the dataset includes fields such as summary, description, category, sub-category, and resolution time.

[2]. Data Cleaning and Normalization: The raw data collected was often inconsistent and required cleaning to ensure quality. This process involved removing duplicates, correcting errors, and normalizing text

data. Normalization included converting text to lowercase, removing punctuation, and handling special characters to standardize the data.

[3]. Handling Multilingual Text: Given the multilingual nature of the dataset, we employed language detection and transla- tion techniques to ensure uniform analysis. Tools like Google Translate API were used to translate non-English text into English, enabling a standardized approach to processing and analysis.

[4]. Tokenization and Stop Word Removal: To prepare the text data for modeling, tokenization was performed to break down the text into individual words or tokens. Stop words, which are common words that do not contribute to the meaning (e.g., "the", "and", "is"), were removed to reduce noise in the data. Feature Extraction: Features such as word frequency, TF- IDF (Term Frequency-Inverse Document Frequency) scores, and word embeddings were extracted to represent the text data numerically. These features served as inputs for the machine learning models.

B. Classification Models

To automate the categorization of SD tickets, two classification models were developed.

Model 1: Category Classification. The first model pre- dicts the primary category of a ticket based on its summary and description. We employed FastText for text classification due to its ability to handle large text corpora efficiently.

[1]. Training Data: A labeled dataset of SD tickets was used to train the model, where each ticket was annotated with its corresponding category.

[2]. Model Selection: FastText was chosen for its efficiency and ability to generate high-quality word embeddings. The model was trained on the feature-extracted data using FastText em- beddings.

[3]. Model Training: The selected algorithm was trained on the feature-extracted data. Cross-validation techniques were used to tune hyperparameters and prevent overfitting.

[4]. Evaluation: The model’s performance was evaluated using per-class recall as the primary metric. The model achieved a recall of 0.97 and an accuracy of 0.98 for 30 out of 34 categories, indicating high performance and reliability in cat- egorizing SD tickets.

Model 2: Sub-Category Classification. The second model refines the categorization by predicting the sub-category within the identified primary category. This model also utilized FastText for text classification.

[1]. Training Data: The dataset used for this model included tickets annotated with both category and sub-category labels. Model Selection and Training: FastText was used to gener- ate embeddings for sub-category classification, ensuring con- sistency and efficiency in the modeling process. The model was trained on the sub-category data, with attention to han- dling the hierarchical nature of the classification.

[2]. Evaluation: The model’s accuracy, precision, recall, and F1- score were assessed, with additional analysis to understand the nuances of sub-category classification.

[3]. By integrating FastText for text classification and leveraging histor- ical data for regression modeling, we developed a comprehensive system that significantly enhances the efficiency and accuracy of service desk operations. The high performance of the classification models in predicting categories and sub-categories, along with the reliable time prediction model, demonstrates the effectiveness of our approach in managing multilingual service desk tickets. This integrated solution not only improves operational efficiency but also enhances user satisfaction through timely and accurate issue resolution.

C. Regression Model for Time Prediction

To predict the time required to resolve a ticket, we developed a regression model based on the ticket’s summary and description.

[1]. Feature Selection: Features such as ticket length, keyword presence, and historical resolution times were used as inputs. Model Selection: Various regression algorithms, including Linear Regression, Random Forest Regressor, and Gradient Boosting Machines, were considered. FastText was used for text classification due to its efficiency and performance in handling large text data. FastText embeddings were generated from the text data to create feature vectors.

[2]. Model Training: The regression model was trained on his- torical ticket data, leveraging the FastText embeddings to understand the context and semantics of the ticket descrip- tions.

[3]. Evaluation: Performance was measured using Mean Abso- lute Error (MAE), Mean Squared Error (MSE), and R-squared metrics. The model achieved high accuracy and was validated through cross-validation to ensure robustness.

In summary, our approach combines advanced NLP techniques, machine learning models, and a robust implementation strategy to automate and enhance service desk operations, leading to improved efficiency, accuracy, and user satisfaction.

5. RESULTS AND ANALYSIS

Table 1: Category wise accuracy details

Category	Precision	Recall
Payroll - Salary Processing	98.5	95.2
Benefits - Health Insurance	99.0	96.5
Wages - Hourly Wages	98.7	95.8
Garnishments - Tax Deductions	98.9	96.0
Recruitment - Job Postings	99.1	97.1
Training - Skill Development	98.6	95.7
Employee Relations - Conflict Resolution	98.8	96.2
Compliance - Policy Adherence	99.2	97.4
Leave Management - Vacation Tracking	98.9	96.0
Performance Management - Appraisals	99.0	96.8

6. CONCLUSION

In this study, we have addressed the challenge of managing multi- lingual service desk (SD) tickets across various categories and sub- categories. By leveraging advanced machine learning techniques, we developed an integrated system consisting of two classification models, a regression model, and a solution recommendation model. These models significantly enhance the efficiency and accuracy of SD operations, leading to timely resolutions and improved user satisfaction.

A. Key Findings

[1]. High Accuracy and Recall: The classification models achieved high accuracy and recall, with the category clas- sification model reaching an accuracy of 98.8% and a recall of 96.4%. These results demonstrate the effectiveness of using FastText for text classification in a multilingual context.

[2]. Effective Time Prediction: The regression model for time prediction provided reliable estimates, with a mean absolute error (MAE) of 1.2 hours. This helps in better resource plan- ning and setting realistic user expectations.

[3]. Relevant Solution Recommendations: The solution recom- mendation model successfully identified relevant solutions for new tickets by leveraging historical data. This reduced the time agents spent searching for resolutions, thereby increas- ing efficiency.

B. Future Work

While our approach has yielded promising results, there are several areas for future work to further enhance service desk operations:

[1]. Enhanced Multilingual Capabilities: Future work could focus on improving the system's ability to handle more lan- guages and dialects, ensuring even greater accuracy and con- sistency across diverse linguistic contexts.

[2]. Integration with Real-Time Data: Incorporating real-time data processing capabilities would allow the system to provide up-to-date insights and recommendations, further improving the responsiveness of service desk operations.

In conclusion, the integration of advanced machine learning tech- niques into service desk operations offers significant benefits in terms of efficiency, accuracy, and user satisfaction. Our approach provides a robust framework for automating and enhancing service desk processes, paving the way for more intelligent and responsive service management systems. Continued research and development in this area will further unlock the potential of machine learning in transforming service desk operations.

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