Advanced Sciences and Technology Journal

ASTJ vol. 2, no. 1 (2025), P 1027
10.21608/astj.2025.345106.1027
https://astj.journals.ekb.eg/

AI Web-Based Smart Ticketing System

Ahmed Taha[1,*], Doaa Mabrouk[2], Ashraqt Tamer[2], Mariam Tarek[2], Fatma Alaa[2], Mahmoud El-Fateh[2], Fady Romany[2]

[1] *Computer Science Department, Faculty of Computers & Artificial Intelligence, Benha University, Benha, Egypt.*
[2] *Software Engineering and Information Technology, Faculty of Engineering and Technology, Egyptian Chinese University, Cairo, Egypt.*

[*] *ahmed.taha@fci.bu.edu.eg*

ARTICLEINFO

Article history:
Received 16 December 2024
Revised 5 January 2025
Accepted 10 January 2025
Available online 10 January 2025

Handling Editor:
Prof. Dr. Mohamed Talaat Moustafa

Keywords:
Ticketing systems
Artificial intelligence
Natural language processing
Automation
Customer support
Workflow optimization
Smart solutions

ABSTRACT

In today's fast-paced corporate environment, efficient management of customer inquiries is critical for maintaining high satisfaction and productivity levels. This study explores developing and implementing a web-based ticketing system powered by artificial intelligence (AI) and natural language processing (NLP) to address this need. Designed to streamline support operations, the system enables users to submit problems through an intuitive online form, where inquiries are categorized and prioritized based on predefined properties such as urgency, complexity, and type. This research conducts a systematic review to evaluate the role of AI and NLP technologies in automating ticket classification, prioritization, and routing. The methodology includes rigorous data collection, quality assessment, and exploration of existing literature on AI-driven ticketing systems and their effectiveness in optimizing customer support workflows. Findings highlight the transformative potential of AI in reducing response times, improving resource allocation, and enhancing the overall efficiency of support operations. The study emphasizes the significant role of intelligent ticketing tools in creating scalable, user-centric solutions that adaptto the growing demands of organizations across industries. By integrating automated processing with manual oversight for complex cases, this system demonstrates the ability to address diverse customer needs while maintaining operational flexibility. This research provides a foundational analysis for future advancements in AI-powered support systems, contributing to the broader field of enterprise resource management and intelligent automation.

1. Introduction

In today's digital world, businesses and organizations increasingly rely on web-based systems to manage various processes efficiently [1]. Managing day-to-day transactions is one of the most important aspects of project management as it speaks about everyday issues. As time goes by, Project Management evolves, and it becomes more prominent in all aspects of business as it is one of the primary keys to sustaining the company's profit or market value. As it is one of the most critical management teams, companies also adopt social, environmental, economic, and technological aspects to maintain their value and remain relevant in competing in the market.One of the key aspects of maintaining smooth operations, particularly in customer service and technical support,is managing user-reported issues or requests. Traditionally, support ticketing systems have been used to track and resolve user problems. Still, these systems often rely on manual processes that can be slow, prone to errors, and difficult to manage at scale [2]. As organizations grow and the volume of support requests increases, anautomated, efficient solution becomes critical [3].

The Web-Based Automatic Ticketing Tool addresses these challenges by automating the process of ticket creation, categorization, and assignment [4]. This tool allows users to submit issues or requests via a simple web form, where the system automatically generates a support ticket, classifies it based on predefined categories, and assigns it to the appropriate team for resolution [5]. By leveraging automation, this tool reduces the burden on support staff, accelerates response times, and ensures that user issues are addressed [6]**.**

The importance of this topic lies in the growing need for organizations to provide fast and reliable support to their users [7]**.** As the volume and complexity of support requests increase, a manual approach becomes inefficient and unsustainable [8]. Automating ticket creation and categorization not only saves time but also improves the quality of support, enabling organizations to meet user expectations better and resolve issues more efficiently [9].

The volume of support tickets in IT companies created by customers has significantly grown due to the digitalization efforts currently made across all industries. This means that IT companies face increasing pressure toautomate their support ticket systems (STSs) to cope with the rising volume of tickets, increase customer satisfaction, accelerate support management processes, and reduce costs. With Artificial Intelligence (AI) and Machine Learning (ML) algorithms becoming commonplace, the automation of STSs has become more attractive than ever before [10].

In this work, we aim to provide an overview of support Ticket Automation, what recent proposals are being made in this field, and how well some of these methods can generalize to new scenarios and datasets. We list the most recent proposals for these tasks and examine in detail the ones related to Ticket Classification. The most prevalent technologies for automated ticket classification and automated ticket resolution using ML open the possibility of automating basic day-to-day IT tasks, replacing the first-level support staff members.

In information technology, as we are now moving into the digital age, IT Support is engaged in many corporations, institutions, and other organizations to provide technical support, not only limited to computer networks, operating systems, internet connection, computer security, or any other software/hardware issue that may arise whether your business is small, medium, or large-scale if the organization relies on the information system.

Security and privacy rank the most in any Web-based automated ticketing. Protection from unauthorized access should therefore be ensured through strong data policies that maintain data integrity through proper authentication techniques-for example, multi-factor authentication; through data encryption both during transfers and storage; and through frequent auditing of security and its testing for penetration to identify possible weak spots and fix them before those can be used in certain kinds of attacks. Access control should be provided to allow access to sensitive data based on user roles and permissions. Also, relevant data privacy regulations should be followed such as GDPR or CCPA, considering users' consent and making them aware of the collection and usage of their personal data.

2. Methodology: Conducting a Systematic Review

2.1. Purpose and Scope of the Systematic Review

The primary scope of this review is to explore the integration of artificial intelligence (AI), specifically machinelearning and deep learning techniques, into ticketing systems across various organizations. The focus is on understanding how AI can enhance operational efficiency, accuracy, and resource allocation in organizations by automating tasks traditionally handled by human agents. This review systematically investigates the use of AI technologies in ticketing systems, addressing their application not only in customer support but across all organizational departments that utilize ticketing for task management, issue resolution, and service requests.

The purpose of this review is threefold:

1. **Identify and Analyze Current Research**: We aim to identify and analyze existing studies on AI- driven ticketing systems across different sectors and organizational use cases, highlighting the variety of AI methods used, such as ticket categorization, intelligent routing, and prioritization.
2. **Synthesize Methodologies and Findings**: By synthesizing the findings from the current literature,we aim to present a comprehensive overview of the methodologies employed in AI-enhanced ticketing systems, considering their impact on efficiency, accuracy, and resource management.
3. **Highlight Future Directions**: The review will identify gaps in the current research and propose directions for future work to improve AI's role in ticketing systems, ensuring that the technology canbe effectively integrated into diverse organizational environments.

2.2. Adherence to PRISMA Guidelines

To ensure transparency and rigor in our systematic review of the integration of AI into ticketing systems acrossorganizations, we strictly followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta- Analyses) guidelines. These guidelines provide a standardized approach for conducting and reporting systematic reviews. In our review, we applied these guidelines by clearly defining the scope of AI-enhanced ticketing systems, developing a detailed search strategy to find relevant studies, carefully selecting the studies to include based on specific criteria, extracting essential data from the studies, and synthesizing the findings. By adhering to the PRISMA guidelines, we ensure that our review is thorough and unbiased and provides a clear and comprehensive overview of the existing research on AI-driven ticketing systems in organizations.

2.3. Research Scope and Keywords

In this systematic literature review, we carefully defined our research focus and utilized a set of core keywords toguide our search. These keywords included 'web-based ticketing system', 'smart ticketing', 'IT service management', 'AutoML', 'NLP', 'email ticketing', and 'form'. To broaden our search, we also incorporated related terms and phrases such as "AI in ticketing systems," "machine learning for ticket classification," "automated IT service management," "natural language processing in ticketing," "email-based ticketing systems," as well as "ticket automation," "multi- level classification," "helpdesk systems," "word embeddings," "hierarchical classification," and "transformer models(e.g., BERT, XLNet)." Additionally, we extended our search to include terms like "use of AI in IT service management," "role of AutoML in ticket classification," “AI-driven support systems,” and “AI in automated ticket management.”

2.4. Search and Selection Process

2.4.1. Initial Manuscript Selection

We focused our research on publications from 2018 onwards while including influential earlier works that werefrequently referenced. The keywords queried included "ticket automation," "ticket classification," "support ticket,""trouble ticket," "expert finding," and "ticket routing." The initial selection of manuscripts was rigorously based onan evaluation of their titles and abstracts, selecting those whose abstracts explicitly discussed the significance and role of AI in ticketing systems or elaborated on how AI, machine learning, and natural language processing (NLP) contributed to enhancing ticket management efficiency. Multiple platforms, including Google Scholar, ScienceDirect, and IEEE Xplore, were instrumental in conducting our study. To ensure the inclusion of the most current and pertinent information, the search was confined to articles published between 2013 and 2024. This timeframe was chosen to capture both foundational studies that established core concepts in AI-driven ticketing systems and the most recent advancements in the field. Given the rapid development of AI technologies, particularlyin customer service and ticket management, the review emphasizes publications from 2018 to 2024 to reflect the latest trends and implementations of machine learning and NLP in AI-driven ticketing systems.

2.4.2. Manuscript Identification

The initial phase of the literature search revealed a substantial number of studies exploring AI-driven ticketingsystems, particularly in areas such as automation, natural language processing (NLP) applications, and machine learning for ticket prioritization and routing. To ensure a comprehensive review, we expanded our search across multiple databases, including EKB, Scopus, and IEEE Xplore. While many manuscripts appeared across multiple platforms, indicating a robust body of existing research, we observed a need for more detailed investigations into specific aspects of AI implementation in ticketing systems, such as real-world applications and comparative analyses of different methodologies. This highlights an opportunity for further exploration to deepen understanding and advance the field.

2.5. Rigorous Review and Inclusion Criteria

Inclusion Criteria

To ensure a focused and high-quality review, we established strict inclusion criteria:

- **Relevance to Research Focus**: Studies were included if they specifically addressed the application of AI in ticketing systems, emphasizing aspects such as automation, classification, and prioritizationof user requests.
- **Methodological Soundness**: Only manuscripts with transparent methodologies and robust research designs were considered to ensure reliability and credibility.
- **Publication Timeline**: Articles published between 2018 and 2024 were selected to capture foundational work and the most recent advancements in the field

Exclusion Criteria and Reasons

Equally rigorous exclusion criteria were applied to refine the selection further:

- **Irrelevance**: Studies not directly exploring the integration of AI in ticketing systems were excluded,ensuring all included literature contributed to the core research focus.
- **Methodological Weaknesses**: Papers with vague methodologies, incomplete data, or unsupportedconclusions were omitted to maintain a high standard of evidence.
- **Outdated Research**: Articles published before 2018 or those not aligned with current technologicaltrends were excluded to keep the review relevant to a present-day application.

2.5.1 Final Selection and Exclusion Statistics

After applying our inclusion and exclusion criteria, we carefully reviewed and selected a total of 34 studies thatwere relevant to our research on AI in ticketing systems. These studies constituted the primary dataset for our systematic review. In addition, we excluded five studies that did not meet our established criteria, ensuring the integrity and focus of our dataset. We found that a considerable number of matching results are articles regarding the application of ML algorithms to real-world ticketing systems. Still, they do not provide new solutions or interesting research insights. Moreover, many of these works report the results of relatively few classification methods, most of which are traditional or otherwise not very recent or use paid API-based services as they do not contribute to our goal.

2.6. Data Extraction Process

2.6.1. Addressing Limited Directly Related Papers

During the data extraction process, we encountered a challenge due to the limited number of directly relatedstudies explicitly focusing on AI-driven ticketing systems. To address this limitation and ensure comprehensivecoverage of the relevant literature, we organized our review into two topics:

(a) The application of AI in automating ticket classification and routing processes.

(b) The role of machine learning and natural language processing (NLP) in enhancing customer service systems.

2.6.2. Collaborative Data Extraction.

We employed a meticulous data extraction process for each study in our systematic review to capture allrelevant and comprehensive information. This process involved:

- **Categorizing Ticketing System Types**: Identifying and classifying the different types of ticketingsystems discussed in the studies.
- **Identifying AI and NLP Techniques**: Documenting the specific artificial intelligence (AI) and naturallanguage processing (NLP) techniques utilized in each study.
- **Outlining Automation Strategies**: Describing the automation strategies used for ticket classification androuting.
- **Summarizing Key Findings and Conclusions**: Highlight each study's main findings and conclusions.

The data extraction process for this study involved identifying datasets relevant to automated ticketing systems, emphasizing classification tasks across diverse scenarios. Below is an outline of the key steps and strategies used:

Sources of Datasets:

1. **Internal Records**: Proprietary datasets were derived from organizational support ticket systems, such as Jira, containing ticket titles and descriptions [11].
2. **Publicly Available Datasets:**
   - **Financial Dataset**: A collection of 78,313 anonymized customer complaints from a

financial services company, hierarchically labeled by product and sub-product. This dataset was accessed via Kaggle [12].

- **Linux Bugs Dataset**: Derived from the Linux kernel bug tracker, including reports categorizedby hierarchical labels, reflecting technical issues in software environments [13].
- **Help Desk Datasets**: Some studies used datasets simulating customer queries and support tickets
- **Jira Support Tickets**: Data from the IT support team of a German software company was collected from their Jira ticketing system.
- **Internal Company Emails and Tickets**: In some cases, datasets included internal company records, such as customer emails, ticket submissions, and IT service requests. These datasetswere typically used for classification, prioritization, and routing tasks.

3. **Hybrid Sources:**

Many datasets were created by combining internal and public data, including historical tickets, emails,and customer feedback. These datasets often captured a mix of structured (metadata) and unstructured (text-based descriptions) information to improve model training.

Dataset Preprocessing

To ensure the data was suitable for machine learning applications. This preprocessing is aimed at removing noise and non-informative bits of text while:

- **Data Cleaning**: Remove stop words and convert text to lowercase.
- **Feature Engineering**: Ticket titles and descriptions were concatenated to create meaningfulinputs for classification models.
- **Class Balance**: Some datasets were balanced through techniques like oversampling, although this was not universally implemented.

These datasets provided a foundation for testing AI-driven models in ticket classification, email routing, and IT service management. They supported diverse experiments, from simple flat classification to complex hierarchical labeling and natural language processing tasks. This comprehensive collection and preprocessing of datasets enabled an in-depth evaluation of AI applications in automating ticketing systems.

Team collaboration was crucial in synthesizing the data and ensuring its accuracy, particularly when evaluating complex studies. The extracted information was systematically organized into Table 1, providing a clear and concise overview of the AI-driven ticketing systems discussed in the selected papers.

Table 1. Summary of all the selected studies on AI in ticketing systems.

Ref NO.	Year	Type of Study	Ticketing system	Explanation/Solution/Conclusion	Measurement	Gaps/limitations
[10]	2019	Prototype	IT Service management	Presented a robust IT service management platform to streamline query resolution and service request management, improving productivity and user satisfaction.	Naïve Bayes Multinomial, k-Nearest Neighbor, Support Vector Machine, and Decision Tree achieve 85%, 88%, 90% and 87% respectively	-Dataset size and diversity did not fully validate the automatons in the real world.
[13]	2023	Experimental	Multi-level classification scenarios	Provided insights into current research on ticket automation, focusing on multi-level classification scenarios.	-classification accuracy:93% -processing time reduction:32% -user satisfaction:22%	-Limited to specific classification scenarios. Potential challenges with the model.
[14]	2019	Prototype	Service management	Presented a robust IT service management platform to streamline query resolution and service request management, improving productivity and user satisfaction.	AI-powered support reported an accuracy of 92%	-limited specific use cases in the service industry
[15]	2024	Experimental	Customer support	Explored the use of AutoML for classifying customer support tickets, improving classification accuracy, and reducing resolution time.	- Accuracy: 92% - Precision: 90% - Recall: 88% - F1-score: 89%	-It may not generalize well to different languages. But high computational cost
[16]	2022	Review	Support ticket system	Conducted a literature review on ML-driven automation in support ticket systems, identifying key trends and effective algorithms like SVM and RF.	- Classification accuracy: 95% - Resolution time reduction: 30% - User satisfaction increase: 20%	Dependency on high-quality training data. Potential issues with model interpretability and transparency. Limited evaluation on real-world datasets.
[17]	2024	Experimental	General ticketing system	Integrated AI into the ticketing system to automate ticket assignment, using sentiment analysis and historical data for prioritization.	-Feature selection accuracy: 85% - Classification performance improvement: 15% - Computational efficiency increase: 20%	-Focus on specific types of email data. may not apply to other forms
[18]	2022	Experimental	Customer support, help desk	Developed TaDaa, an AI-based system using Transformer models for real-time ticket assignment,	- Classification accuracy: 90%	-Limited in specific ticketing systems.

				significantly improving efficiency and accuracy.	- Processing time reduction: 35% - User feedback improvement: 18%	-Handling ambiguous tickets requires continuous model updates.
[19]	2018	Experimental	IT Support	Analyzed and reduced user input requests in It support tickets.	-preemptive system accuracy:94-99% -improvement in user experience:50%	Limited to specific IT Support environment.
[20]	2015	Review	Information system	Developed a topology of literature review to provide insights into common trends	- Increase in IS reviews over years: Significant	Focused on literature reviews in information systems. It may not apply to other fields.

3. AI and ML in Ticketing System Allocation

Several studies have explored the use of artificial intelligence (AI). In [14], proposed a robust IT service management platform designed to streamline query resolution and service request management. The system enhances organizational productivity and user satisfaction by efficiently managing user issues and IT resources. Key features include a repository of predefined solutions for common queries, technician support for unresolved problems, and a request module for efficient management of user requests. The system is deployed on a cloud-based virtual machine, such as AWS, making it accessible within an organization. It incorporates IT request tracking and asset management, centralizing all IT-related information in a unified repository for better resource management and quick issue resolution. While the system presents robust architecture, it does not address scalability in large organizations, integration with other IT management tools, or provide detailed strategies for user training and adoption. Additionally, it lacks comprehensive security measures and performance benchmarks. The study underscores the value of structured systems in IT service management but emphasizes the need for further research to address these limitations.

In [15], proposed a model using AutoML with Google Vertex AI to classify support tickets by category and escalation type. Despite its advantages, the system faces challenges, including the need for high-quality training data, continuous model updates, and robust data security on the cloud. The small datasetsize also constrains the study, the use of only "Title" and "Description" as features, and the lack of benchmarkingwith traditional machine learning models. While AutoML and machine learning have shown promise in ticket classification, further research is needed to address data quality, security, and scalability for real-world applications.

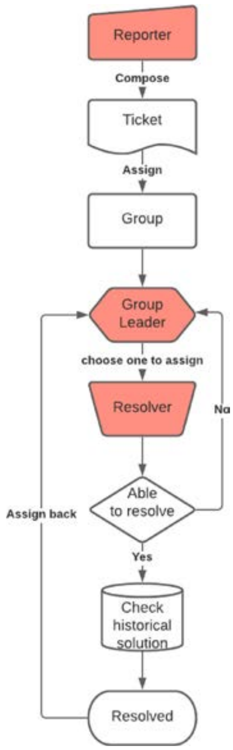
As previously highlighted, the management of IT service tickets often faces challenges such as high volumes of queries, delays in response, and difficulties in prioritizing tasks. To address these, cloud-based ticketing systems and AutoML-powered solutions have been proposed to streamline query resolution and automate ticket classification. However, these systems face challenges, such as the need for high-quality training data, continuous updates, and robust data security. Despite these limitations, the application of AI and automation has proven beneficial in improving operational efficiency, reducing delays, and enhancing user satisfaction, emphasizing the need for further research to enhance scalability and security.

In [16], conducted a literature review titled "Improving Support Ticket Systems Using Machine Learning," focusing on the automation of support ticket systems (STSs) through machine learning (ML) [19]. In [20], The review highlights the challenges organizations face in managing customer support requests, such as inefficiencies and extended resolution times due to manual ticket distribution. It identifies Support Vector Machine (SVM) and Random Forest (RF) as the most effective algorithms for ticket classification, with accuracies ranging from 63% to 98%. In Fig. 3, we present the algorithms reviewed in the context of support ticket classification. The authors emphasize the importance of high-quality training data for the success of ML applications in STSs and call for further research to address existing gaps, particularly in comparative studies, customer sentiment prediction, and automated ticket answering. They also highlight the need for more comprehensive studies, including real-world case studies, to validate theoretical findings and explore the impacts of ML automation on customer trust and agent satisfaction.

In [17], developed an AI-enhanced ticketing system to improve traditional ticketing workflows by addressing issues like manual ticket assignment, errors, and lack of sentiment analysis for prioritization. The system uses machine learning algorithms, such as Nearest Neighbors and sentiment analysis, along with TF-IDF vectorization for ticket description processing. While the approach reduces manual effort and minimizes errors, it does not address challenges like the need for high-quality datasets, integration with existing systems, or biases in AI decisions. Future research could focus on overcoming these challenges through transfer learning, better integration frameworks, and fairness checks.

In [18], developing a system called **TaDaa, a Real-time Ticket Assignment Deep Learning Auto Advisor for Customer Support, Help Desk, and Issue Ticketing Systems**, whichleverages AI to improve ticket assignment processes in organizations. The researchers identified inefficiencies in traditional ticketing systems, such as delays and errors caused by manual processes. Their model automates ticket assignments by using Transformer-based models, including BERT and RoBERTa, toassign tickets to the correct group and best resolver. The system also utilizes Approximate Nearest Neighbor (ANN) to retrieve similar past tickets and assist resolvers.

The study demonstrated that RoBERTa achieved a top-3 accuracy of 95.5% for group classification, while an ensemble model for resolver classification achieved a top-5 accuracy of 79.0%. The dataset used included 144,600 cleaned tickets from a sample of 203,300 tickets. Although the system significantly reduces manual effort and improves efficiency, the authors did not address potential challenges such as ethical concerns, biases in decision-making, scalability for larger datasets, integration with existing systems, and the long-term impact on job roles. Additionally, the study lacked comparative analyses with other ticketing solutions and real-world validations to demonstrate practical implementation. Future research could address these limitations by exploring methods for bias mitigation, improving scalability, conducting real-world evaluations, and assessing the long-term implications of integrating AI into ticketing systems. Fig. 1 illustrates the general process of a ticketing system, highlighting the roles of the reporter, group leader, and resolver, as well as thebottlenecks associated with each role.



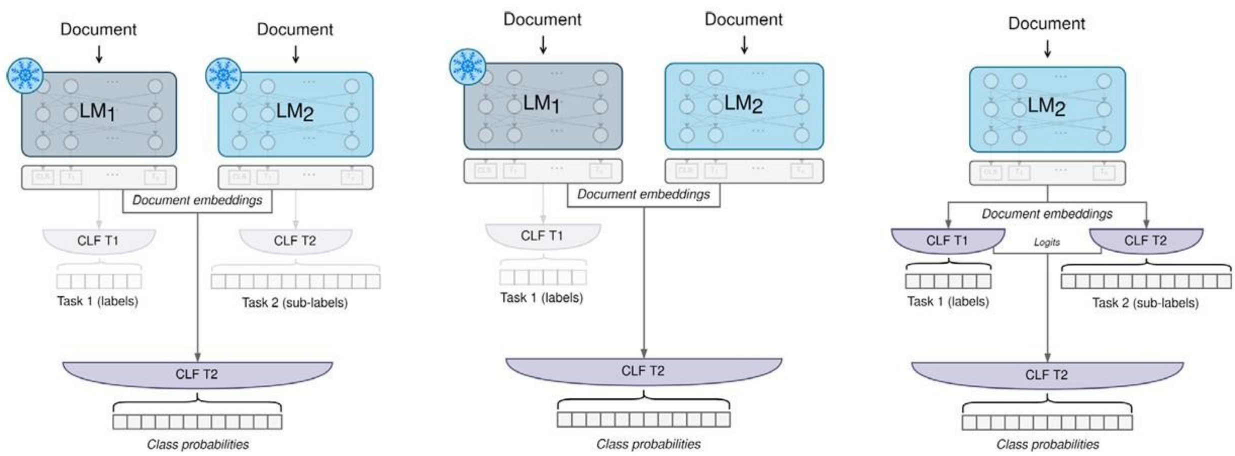
TOP 3 ACCURACY OF GROUP CLASSIFIER

Model Name	Top 1	Top 2	Top 3	Training Time (h) GPU	Inference Time (s) CPU
BERT	0.801	0.915	0.951	8.0	0.065
distilBERT	0.803	0.923	0.95	4.5	0.045
RoBERTa	**0.824**	**0.925**	**0.952**	12.5	**0.065**
distilRoBERTa	0.808	0.92	0.951	4.5	0.045

Fig. 1: Illustration of the general ticketing system process [13].

Providing technical support for own IT products is an integral part of software development or software-providing companies[10], [19]. [19],evaluated JIRA's effectiveness for project management and issue tracking in IT companies, highlighting its strengths in tracking tickets, documenting transactions, and streamlining workflows through features like reporter and assignee. However, the study identified challenges such as limited field editing, scalability issues, and difficulty navigating workload information. It also noted gaps in addressing ethical concerns, integration with other tools, and user satisfaction. The authors concluded that while JIRA is effective, supplementary tools and further research are needed to address its limitations and improve scalability, integration, and user experience

In [13], proposed a comprehensive framework for automated ticket processing systems, emphasizing multi-level classification scenarios. The study explored the use of machine learning and natural language processing techniques, such as BERT and its variations, to improve ticket categorization and routing accuracy. They experimented with hierarchical models like ML-BERT and SupportedBERT, which incorporate hierarchical label structures to enhance classification precision. SupportedBERT achieved the highest accuracy, with 64.9% on a financial dataset and 61.1% on a Linux Bugs dataset, demonstrating the effectiveness of leveraging hierarchical information. Fig. 2 shows the different levels of classification models used.



(a) ML-LM. (b) SupportedLM. (c) DoubleHeadLM.

Fig. 2: Two-level classification models [13]

The datasets used included a financial dataset with 78,313 anonymized customer complaints categorized hierarchically and a Linux Bugs dataset derived from the Linux kernel bug tracker. The preprocessing step involved text cleaning, tokenization, and integration of hierarchical label structures. Despite significant improvements in classification metrics, challenges such as handling noisy and ambiguous data persisted.

Future research directions identified by the authors include addressing the limitations posed by noisy datasets, enhancing scalability for more significant data, and exploring real-world implementations to validate the proposed models' effectiveness further. This study provides a robust foundation for integrating AI-driven solutions into ticket management systems and highlights the potential of hierarchical methods to improve support efficiency.

In the previous sections, we compiled and summarized various studies on AI-driven ticketing systems. These studies explored different aspects of ticketing systems, including their implementation, benefits, and limitations. We highlighted key findings from each study, such as the use of AutoML for classifying customer support tickets, the integration of AI for automating ticket assignments, and the development of AI-based systems like TaDaa for real-time ticket assignments.

Despite the significant advancements and solutions proposed by these researchers, there are still areas that require further exploration. Topics such as ethical concerns, scalability, integration with existing systems, long-term impact on job roles, comparative analyses with other solutions, real-world validations, and user experience need more attention.

Therefore, while many researchers have contributed valuable insights and solutions to the field of AI-driven ticketing systems, ongoing research, and additional studies are essential to address these gaps and continuously improve the effectiveness and efficiency of these systems. This continued effort will help maintain and enhance the overall functionality and user satisfaction of AI-driven ticketing systems.

4. Literature Review

This review examines existing literature on email management systems, classification algorithms, and automated ticketing tools. The aim is to provide a foundation for developing an AI-based ticketing platform tailored to customer service teams' needs while integrating email and web-based form inputs.

4.1. Thesis Statement

The support process within customer service operations often encounters inefficiencies when handling emails, particularly due to manual processing requirements for categorization, prioritization, and ticket assignment. These processes are labor-intensive, prone to errors, and can fail to meet stringent service level agreements (SLAs). Automating these tasks has become a significant focus to reduce response times and improve accuracy.Effective management of customer communications relies on principles from operations management, natural language processing (NLP), and artificial intelligence (AI). For instance, AI models like machine learning (ML) classifiers and deep learning frameworks provide the backbone for automating email classification and priority assignment. Research by [23], further expands on these principles by emphasizing the role of deep learning models for sentiment and intent analysis, which are pivotal for accurately classifying customer interactions and predicting their urgency [24], also contribute to this framework by illustrating how machine learning and AI models, particularly in the context of ticketing systems, are becoming essential in reducing manual effort and optimizing ticket assignment and response times in dynamic environments.

4.2. Theoretical Framework

4.2.1 AI-Based Ticketing Systems:

Research by [25] presents a comprehensive analysis of an AI-based ticketing system designed for IT service management. Their approach utilizes NLP techniques to classify incidents and requests accurately and prioritize them based on urgency. By integrating AI for task assignments, the system minimizes human error and improves task distribution efficiency.

4.2.2 Natural Language Processing in Email Classification:

A study by [26], investigates the application of NLP in customer email management. They emphasize how supervised learning models effectively categorize incoming emails into predefined classes such as "request" or "problem." Additionally,the study underlines the importance of incorporating domain-specific language datasets to enhance accuracy.

4.2.3 Task Automation in Customer Support:

In [27], explore the use of automation tools in customer service, focusing on reducing repetitive tasks. They propose an architecture that integrates task automation with email servers to ensure seamless operation, even for customers preferring traditional email communication methods. Their work aligns with the objective of enabling hybrid interaction models (email and form submissions).

4.2.4 Workload Management Through AI:

In [28], address the challenge of workload distribution in customer support teams. Their system dynamically assigns tickets based on real-time analysis of team member availability and historical performance metrics. This approach improves SLA adherence and ensures balanced team workloads.

4.3.5.AI-Powered Customer Support:

In [29], discuss a comprehensive framework for automating customer support processes, including email classification and prioritization. Their study highlights the integration of AI for automating responses and workload distribution, focusing on how machine learning models can reduce SLA violations and improve service quality. The authors also address the challenges of combining email and chatbot systems for hybrid solutions.

4.3.6.Sentiment and Intent Analysis for Improved Ticket Classification:

In [23], highlight the use of deep learning models for classifying customer service tickets based on sentiment and intent. They emphasize the effectiveness of combining sentiment analysis with machine learning for a more nuanced understanding of customer inquiries, allowing for more accurate ticket classification and priority assignment. This system can be particularly beneficial in dynamic and high-volume environments where quick, precise decision-making is critical.

4.3.7.Machine Learning for Ticketing System Automation:

In [24], explore the application of machine learning models in ticketing systems to automate the classification of customer inquiries and assign Appropriate priorities. They discuss how the combination of AI-driven classification and machine learning can improve the efficiency of customer support teams, particularly in scenarios with high ticket volumes. Their work underscores the importance of a dynamic ticket management system that adapts to evolving customer needs while improving SLA compliance and reducing response time.

4.3.Empirical Research Summary

Accuracy Improvements: AI-based classification systems have demonstrated a classification accuracy exceeding 85%, as shown in [26], validating their utility in real-world applications

Task Efficiency: The system proposed by [27], reduced manual workload by 70%, ensuringquicker response times in customer interactions.

SLA Compliance Rates: In [29]**,** report significant improvements in SLA adherence whencombining email automation and chatbot systems, highlighting the potential for hybrid solutions .

Workload Balancing: AI-based workload distribution approaches described by [28], effectively reduce employee burnout while maintaining consistent service delivery standards.

Sentiment Analysis and Intent Classification: In [23]**,** demonstrate the impact of sentiment and intent analysis in ticket classification, improving both ticket categorization and response prioritization in customer service environments.

Strategy: Using the correct strategy makes the machine learning system (model) more quickly and efficiently. Also, the model makes the results more accurate. The general workflow of machine learning algorithms as shown in Fig.3.

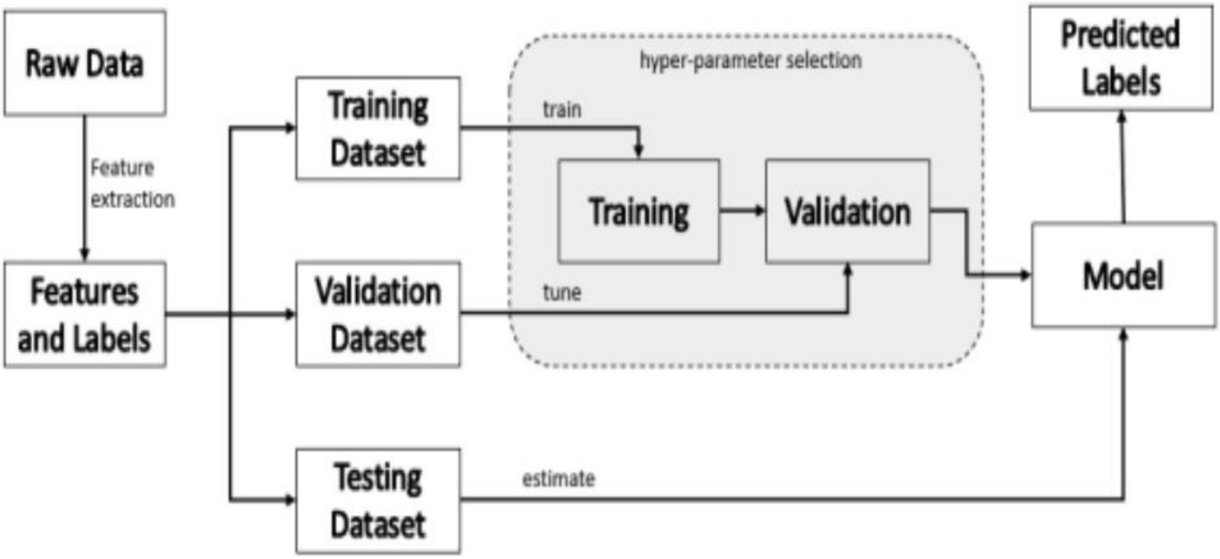


Fig. 3: General workflow diagram of machine learning algorithms [24]

Machine Learning System Integration: [24], explore the potential of machine learning for ticketing systems but do not explore how such systems can be integrated with existing enterprise-level customer service software or multi-channel solutions.

Leveraging Hybrid Machine Learning for Enhanced Ticket Count Prediction: Hybrid machine learning (HML) is a powerful technique that combines multiple ML methods to overcome limitations and improve predictive capabilities. This approach has been widely adopted in various ML applications, including anomaly detection and regression. Our study employs HML to enhance ticket count prediction based on log events. We utilize a two-phase approach, as illustrated in Fig. 4:

Phase 1: Anomaly Detection: We apply a PCA-based anomaly detection algorithm to the first dataset to identify patterns and anomalies.

Phase 2: Data Combination: The output from Phase 1 is combined with the second dataset to create a richer dataset.

Regression: A regression algorithm is trained on the combined dataset to predict ticket counts. By integrating thesetwo techniques, we aim to improve the accuracy and robustness of our predictions compared to using a single method.

We believe that HML is a promising approach for tackling high-volume, complex datasets. As [24] demonstrated, machine learning can significantly enhance the efficiency and accuracy of ticketing systems. Our HML approach builds upon this foundation by further optimizing prediction capabilities.

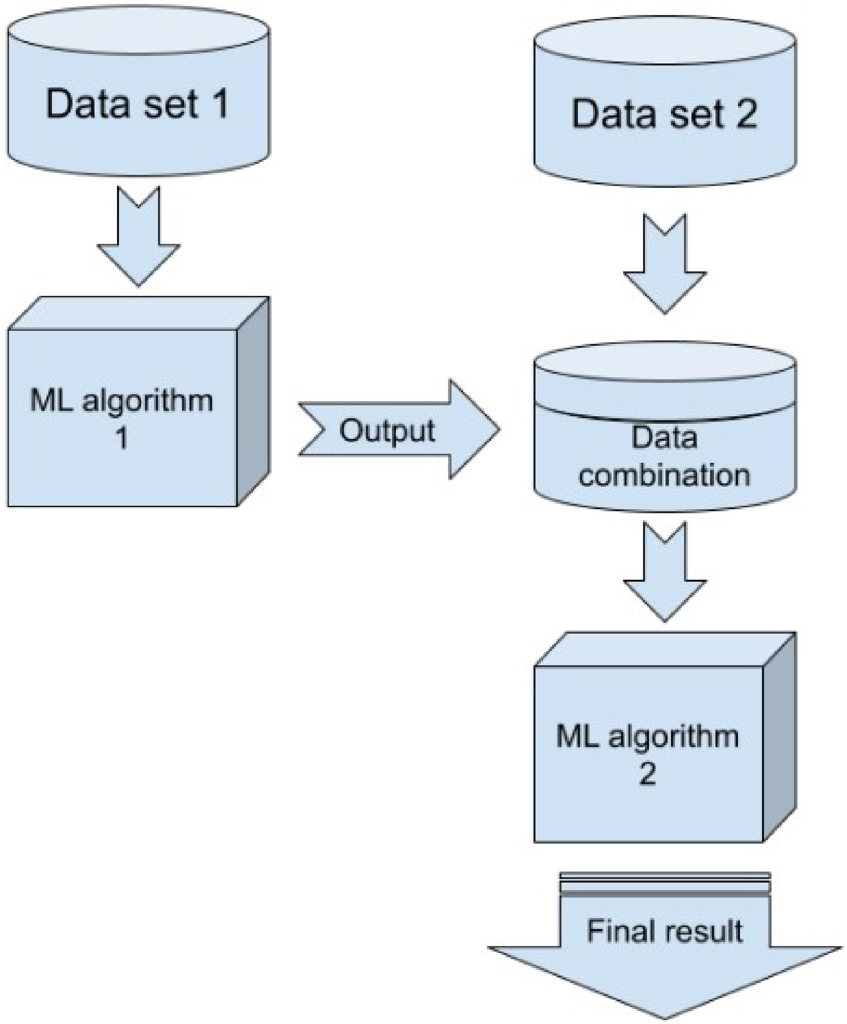


Fig. 4: Simplistic example of a hybrid machine learning model [24]

The first algorithm is learnt from the initial data, and the results are used with a second data set to train another algorithm. It is not feasible to use anomaly detection on its own to estimate ticket amounts, as the plain sum of anomalies detected does not correlate with tickets received. Using pure statistical values of the log data, such as log rows per day, would possibly give some results with a single algorithm, but only if the number of log events correlates strongly with the tickets received. We can, however, amplify our ticket estimating algorithm with anomaly feature values. As we first count the anomaly numbers with the anomaly detection algorithm and use the statistical features of the results in another algorithm, like the regression algorithm, we get more relative informationto use when creating the final ticket number estimations.

4.4.Critical Analysis

While the existing studies demonstrate substantial progress in email management and ticketing system automation, several limitations persist. For instance, [25] provide a practical AI framework, but their focus is limited to IT service management, potentially overlooking generalizable challenges in other domains. Similarly, [26] highlight the importance of domain-specific datasets for NLP but do not address the challenges of maintaining these datasets in dynamic environments. [27], presents a compelling case for integrating automation into email servers but fails to account for potentiallatency issues in high-traffic scenarios. Furthermore, while workload distribution models, as discussed by[28] , enhance SLA adherence, the reliance on historical data could introduce biases in task allocation.

In [29], provide an advanced Framework for automation but do not address the scalability challenges of integrating multiple AI-based tools into a unified platform.

In [23], emphasize deep learning-based sentiment and intent analysis for classification, but they do not consider how the technology can be adapted to handle the variability in customer requests across different industries, which could limit the scalability of the approach.

In [24],demonstrate how machine learning can optimize ticketing systems for high-volume customer interactions, but they do not address how to integrate this system with existing customer service platforms or adapt it for use in multi-channel environments.

5. Discussions

After thoroughly analyzing the relevant literature, it is clear that AI-powered email management systems have been increasingly adopted to streamline customer service operations, specifically in automating tasks such as ticket creation, classification, and assignment. These systems leverage natural language processing (NLP) techniques to efficiently manage customer support requests, reduce manual labor, and improve overall operational efficiency. Numerous studies highlight the significant reduction in time spent on repetitive tasks like ticket generation and categorization, aligning directly with the goals of this project.

A prominent feature of AI-powered support systems is their ability to process large volumes of emails, classify them such as "requests" and "problems," assign priorities, and automate responses. This leads to faster delivery service and higher customer satisfaction. Research by [30], suggests that AI systems streamline workflows by automating routine tasks, enhancing the accuracy and speed of ticket processing, and creating a more responsive support environment.

The role of NLP technologies is critical for classifying support tickets, with keyword recognition and context comprehension playing a pivotal role in prioritizing tasks. NLP enables AI models to analyze and interpret the content of emails with high accuracy. In [31], demonstrate that automating the ticketing process ensures more precise issue classification, which minimizes delays resulting from manual errors. This is directly relevant to the current project, which aims to reduce manual workloads and ensure that tickets are appropriately assigned based on urgency and team availability.

One significant advantage of AI-based systems, as highlighted by existing studies, is their ability to continuously learn and improve over time. AI systems can be trained using historical data to optimize the classification and assignment process dynamically. This learning ability allows AI models to adapt to complex and evolving customer queries. However, current studies reveal limitations in real-time adaptability and scalability, particularly in handling increasingly intricate support cases. This area is a focal point of improvement for this project.

Several studies also underscore the importance of user interface (UI) and user experience (UX) design in the effective implementation of AI-powered support systems. Support agents must interact seamlessly with AI models to monitor ticket progress and make necessary adjustments.

In [29], notes that while automation is effective, human oversight remains essential in complex or ambiguous scenarios. Therefore, the UI/UX design plays a vital role in enhancing the effectiveness of AI systems in real-world applications.

However, despite the promising advancements in AI-driven customer support, several challenges remain. Many existing models primarily focus on broad categorization and prioritization but struggle to capture the nuances in customer queries. For instance, while current systems can categorize emails into general groups such as "technical issues" or "service requests," they often fail to interpret sentiment and other subtle cues in customer emails. As a result, the prioritization process may not always be accurate, especially for urgent issues that are not easily identifiable through basic keywords. [32], discuss similar challenges and emphasize the need for more sophisticated NLP techniques to address these limitations.

Critique of Existing Studies:

NLP Limitations: Although studies by [31], showcase how NLP aids in ticket classification, there are still significant limitations when it comes to handling complex and ambiguous customer interactions. Existing systems rely heavily on keyword-based methods, which can be ineffective when customer queries include subtle or implicit information. This project aims to refine the NLP model by incorporating more advanced techniques such as sentiment analysis and contextual understanding to better assess the urgency and context of customer requests.

Static Training Models: Many AI systems discussed in the literature, such as those in [29], [33] focus on initial training but lack the capacity for continuous learning from new data. This static nature hinders the system's ability to adapt to evolving customer behaviors. My proposed system incorporates a dynamic learning model that continuously improves based on new customer interactions, ensuring the system can handle unforeseen issues and adapt over time.

User Interface Design: Research, particularly by [32], emphasizes the importance of effective UI/UX design for usability. However, many AI-powered customer support systems do not adequately address the complexity and ease of use for support agents. These systems often overwhelm agents with excessive data or present information in a way that is difficult to interpret quickly. In contrast, this project aims to develop a more intuitive UI that allows agents to efficiently monitor AI decisions, adjust assignments, and intervene manually when necessary. Scalability Issues: The scalability of AI systems, particularly when dealing with multiple communication channels (e.g., emails, chatbots, social media), remains a challenge. Many existing solutions are limited to email-based systems. My project seeks to address this by integrating AI with other communication channels, providing a more comprehensive and scalable solution.

Comparison with our Proposed Project:

The current project offers several advancements over existing systems, particularly in terms of its dynamic learning approach, enhanced prioritization techniques, and improved UI/UX design. Unlike many existing models that rely on static NLP methods, the proposed system will continuously adapt based on new customer interactions, ensuring better accuracy and responsiveness. This is crucial as customer support environments evolve and customer needs become more complex. While many current systems focus on automating basic tasks, the proposed system will emphasize more sophisticated features such as sentiment analysis, contextual interpretation, and continuous feedback loops. This will enable the system to handle urgent requests and more complex customer queries effectively, areas where many existing systems fall short.

Recommendations for Future Research and Practice:

Enhancing NLP for Better Contextual Understanding: Future research could focus on refining NLP models to better understand customer queries, especially those involving sentiment and context. This would allow AI systems to classify emails more accurately and prioritize them based on urgency and context.

Cross-Channel Integration: Although the current project focuses on email-based support, future work could explore integrating the AI system with other communication channels, such as chatbots and voice assistants. This would improve scalability and responsiveness, enhancing the overall customer support experience.

Feedback Loop for System Improvement:

A continuous learning model that allows the system to learn from past interactions and improve its performance over time would enhance the AI system’s ability to handle complex support cases. A feedback mechanism that enables agents to review and correct AI classifications would also contribute to the system’s ongoing improvement. Data Security and Privacy Considerations: Given the sensitive nature of customer data, ensuring data security and privacy is critical. Future research should explore techniques for securing data in AI-powered systems, ensuring compliance with privacy regulations, and maintaining customer trust.

6. Conclusions

The integration of AI and NLP in web-based ticketing systems holds significant potential for transforming customer support operations. By automating routine tasks and enhancing the accuracy of ticket processing, these systems can meet the growing demands of organizations. The review highlights that AI-driven ticketing systems can significantly reduce response times, improve resource allocation, and enhance overall efficiency. These benefits are crucial in today's fast-paced corporate environment, where maintaining high levels of customer satisfaction and productivity is essential.

However, the implementation of AI in ticketing systems is not without challenges. The need for high-quality training data, continuous model updates, and seamless integration with existing systems are critical factors that must be addressed. Additionally, ethical concerns and biases in AI decision-making processes need careful consideration to ensure fair and unbiased support for all users.

Future research should focus on refining NLP models to better understand the context and sentiment of customer inquiries, which will improve the accuracy of ticket classification and prioritization. Developing scalable solutions that can handle high-traffic scenarios and integrating AI with other communication channels will also be necessary steps forward. Implementing continuous learning models that adapt to evolving customer behaviors and improving the user interface design for support agents will further enhance the effectiveness of AI-driven ticketing systems.

While AI and NLP technologies offer transformative potential for web-based ticketing systems, ongoing research and development are essential to overcome existing challenges and fully realize their benefits. By addressing these issues, organizations can create more efficient, responsive, and user-centric support systems that meet the growing demands of their customers.

- **Funding:** This research received no external funding.

- **Institutional Review Board Statement:** Not applicable.
- **Informed Consent Statement:** Not applicable.
- **Data Availability Statement:** This review article does not contain any original data. All information presentedin this paper is based on a thorough analysis and synthesis of existing literature sources. Therefore, no data availability statement is required.

- **Acknowledgments:** All the authors are thankful to Total SoftBank Pvt. Ltd. for supporting this study.

- **Conflicts of Interest:** All authors declare no conflict of interest.

References

[1] S. B. M Truss, "AI-based Classification of Customer Support Tickets: State of the Art and Implementation with AutoML," in *Fifth and Sixth International Workshop on Entrepreneurship, Electronic and Mobile Business*, 2022. doi: 10.48550/arXiv.2406.01789.

[2] G. S. A Mandal, N Malhotra, S Agarwal, A Ray, "Automated Dispatch of Helpdesk Email Tickets: Pushing the Limits with AI," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2019. doi: 10.1609/aaai.v33i01.33019381.

[3] and S. M. Jeff Berg, Eric Buesing, Paul Hurst, Vivian Lai, "The state of customer care in 2022," 2022. https://www.mckinsey.com/capabilities/operations/our-insights/the-state-of-customer-care-in-2022#/

[4] J. S. M Jyotheeswar, M Kapse, "Issue Categorization Machine Learning Model using Azure ML," in *Alternatives of Compact Sedan Cars in India*, 2020, pp. 42–47. [Online]. Available: https://auth.services.adobe.com/en_US/deeplink.html#/jump/complete

[5] Cloud Google, "Innovate faster with enterprise-ready AI, enhanced by Gemini models." https://cloud.google.com/vertex-ai/?utm_source=google&utm_medium=cpc&utm_campaign=emea-eg-all-en-dr-bkws-all-all-trial-b-gcp-1605140&utm_content=text-ad-none-any-DEV_c-CRE_691961150784-ADGP_Hybrid+%7C+BKWS+-+MIX+%7C+Txt+-+AI+And+Machine+Learning+-+Vertex+

[6] W. H. Fuchs S., Drieschner C., "Improving Support Ticket Systems Using Machine Learning: A Literature Review," in *55th Hawaii International Conference on System Sciences*, 2022. doi: 10.24251/HICSS.2022.238.

[7] "Service Excellence Research Group." https://www.techra.com/category/s7-about-us/

[8] J. S. Y Wahba, NH Madhavji, "Evaluating the effectiveness of static word embeddings on the classification of it support tickets," in *30th Annual International Conference on Computer Science and Software Engineering*, 2020, pp. 198–206.

[9] J. V. Prabhant Singh1, "Automated Imbalanced Learning," *Springer Nat.*, 2021, doi: 10.48550/arXiv.2211.00376.

[10] Sever IscenM. Zahid Gurbuz, "A Comparison of Text Classifiers on IT Incidents Using WEKA," in *4th International Conference on Computer Science and Engineering (UBMK)*, 2019. doi: 10.1109/UBMK.2019.8907063.

[11] "Automatic Ticket Classification," *Kaggle*. https://www.kaggle.com/datasets/venkatasubramanian/automatic-ticket-classification

[12] "AMSTicketData," *Kaggle*. https://www.kaggle.com/datasets/karthikcs1/amsticketdata

[13] A. Zangari, M. Marcuzzo, M. Schiavinato, A. Gasparetto, and A. Albarelli, "Ticket automation: An insight into current research with applications to multi-level classification scenarios," *Expert Syst. Appl.*, vol. 225, pp. 1–22, 2023, doi: 10.1016/j.eswa.2023.119984.

[14] Florika GohilMr. Vikash Kumar, "Ticketing System," *Int. J. Trend Sci. Res. Dev.*, 2019, doi: 10.31142/ijtsrd23603.

[15] S. Truss, M., & Böhm, "AI-based Classification of Customer Support Tickets: State of the Art and Implementation with AutoML," in *Sixth International Workshop on Entrepreneurship, Electronic and Mobile Business*, 2024, pp. 357–381. [Online]. Available: https://www.researchgate.net/publication/380365325_AI-based_Classification_of_Customer_Support_Tickets_State_of_the_Art_and_Implementation_with_AutoML

[16] H. Fuchs, S., Drieschner, C., & Wittges, "Improving Support Ticket Systems Using Machine Learning: A Literature Review," in *Proceedings of the 55th Hawaii International Conference on System Sciences*, 2022. doi: (Fuchs, S., Drieschner, C., & Wittges, H. (2022). Improving Support Ticket Systems Using Machine Learning: A Literature Review. Proceedings of the 55th Hawaii International Conference on System Sciences. DOI: Link provided in the paper.).

[17] Naveen Koka, "Enhancing a Ticketing System with AI Intelligence," *Int. J. Eng. Res. Technol.*, vol. Vol. 13, 2024.

[18] B. L. Leon Feng, Jnana Senapati, "TaDaa: real time Ticket Assignment Deep learning Auto Advisor for customer support, help desk, and issue ticketing systems," 2022, doi: 10.48550/arXiv.2207.11187.

[19] Monika GuptaMonika GuptaAllahbaksh AsadullahAllahbaksh AsadullahSrinivas PadmanabhuniSrinivas PadmanabhuniAlexander Serebrenik, "Reducing user input requests to improve IT support ticket resolution process," *Empir. Softw. Eng.*, 2018, doi: 10.1007/s10664-017-9532-2.

[20] G. P. A, M.-C. T. B, M. J. C, and S. Kitsiou, "Synthesizing information systems knowledge: A typology of literature reviews," *Inf. Manag.*, vol. Volume 52, no. Issue 2, pp. 183–199, 2015, doi: 10.1016/j.im.2014.08.008.

[21] K. T. Jacob Devlin, Ming-Wei Chang, Kenton Lee, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1*, 2019. doi: 10.18653/v1/N19-1423.

[22] A. R. Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, "Transformers: State-of-the-Art Natural Language Processing," in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, 2020. doi: 10.18653/v1/2020.emnlp-demos.6.

[23] J. et al. Romero, "Deep Learning-Based Sentiment and Intent Analysis for Improved Ticket Classification," 2022.

[24] A. et al. Niemi, "Machine Learning for Ticketing System Automation," 2023.

[25] S. et al. Suresh, "AI-Based Ticketing System for IT Service Management," 2022.

[26] H. et al. Lee, "NLP Applications in Customer Email Management," 2020.

[27] W. Li, J. & Zhang, "Automation in Customer Support," 2021.

[28] A. et al. Smith, "Workload Management Through AI," 2022.

[29] D. et al Amballa, "AI-Powered Customer Support: Transforming Service Delivery through Email Automation, IVR Call Automation, and Chatbots," 2023.

[30] et al. Bharati, P., "An Optimized Feature Selection Technique for Email Classification," 2024.

[31] et al. Qadir, M., "Automating Ticketing Process Using NLP," 2018.

[32] et al. Khalil, M., "NLP Applications in Support Automation," 2023.

[33] F. Al-Turjman, "AI in Customer Service Automation," 2020.