Capstone Project Proposal

<Your Name Here>

Business Goals

Project Overview and Goal What is the industry problem you are trying to solve? Why use ML/AI in solving this task? Be as specific as you can when describing how ML/AI can provide value. For example, if you're labeling images, how will this help the business?	Project Idea: Automated Customer Support Ticket Classification using Machine Learning Organizations in the customer service sector struggle with manually classifying and directing a significant volume of support tickets, resulting in delays and disgruntled consumers. This challenge will be addressed by adopting Automated Customer Support Ticket Classification utilizing Machine Learning (ML) and Artificial Intelligence (AI). Learning from past data allows ML systems to accurately categorize tickets based on patterns and keywords. This automation improves efficiency, reduces response times, and reduces misrouted inquiries. Scalability is attained without requiring a linear increase in resources, and enhanced ticket handling increases customer happiness and loyalty. Historical data analysis also gives useful insights into prevalent consumer complaints for a proactive response. By minimizing manual ticket processing, the company saves money and improves support operations, resulting in simplified procedures and better customer service.
Business Case Why is this an important problem to solve? Make a case for building this product in terms of its impact on recurring revenue, market share, customer happiness, and/or other drivers of business success.	Customer Service Automation Ticket Classification with Machine Learning (ML) and Artificial Intelligence (AI) addresses a key issue with major financial ramifications. Organizations may gain faster response times and more accurate ticket routing by deploying this system, resulting in enhanced customer satisfaction and loyalty. Customers who are satisfied with the company's products or services are more likely to continue using them, lowering customer churn, and increasing recurring income. Furthermore, the system's efficiency distinguishes the company from competitors, favorably

	boosting market share growth. Customers that are satisfied with a brand become brand champions, influencing others' purchase decisions and contributing to total consumer pleasure. The automation of support resources leads to cost savings and increased productivity. Historical ticket data analysis gives significant insights into reoccurring customer complaints, enabling preemptive efforts to solve frequent issues and improve customer experiences. The ML/AI system can quickly scale to meet expanding needs as the business grows, providing efficient and effective support operations. Overall, the accomplishment of this initiative may improve the company's reputation, encourage consumer loyalty, and propel long-term financial success.
Application of ML/AI What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve?	The precise task that ML/AI will do is automatic customer assistance ticket categorization. Using ML algorithms to examine past ticket data, the system will properly categorize incoming support tickets based on patterns and keywords. The business consequence will be faster response times, fewer misrouted inquiries, enhanced customer satisfaction, and better resource utilization. This automatic ticket classification will expedite support operations, improve customer experiences, and generate long-term company success by cultivating customer loyalty and favorable word-of-mouth recommendations. Furthermore, the system's scalability provides effective support handling as the organization grows, adding to overall operational efficiency and market competitiveness.

Success Metrics

Success Metrics What business metrics will you apply to determine the success of your product? Good metrics are clearly defined and easily measurable. Specify how you will establish a baseline value to provide a point of comparison.	The product's performance will be monitored using several clearly defined and easily measurable business KPIs. Customer satisfaction ratings, average response time, issue resolution rate, and customer churn rate are all important indicators. To create a baseline value, data from the time preceding the introduction of the automated ticket categorization system will be gathered and examined. This historical data will be used to compare performance before and after installation. The organization may analyze the product's efficacy in enhancing customer support operations and attaining the intended outcomes by recording and comparing these indicators over time, assuring continual progress and success.

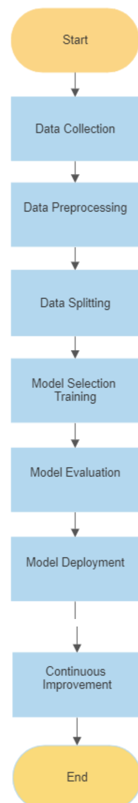
Data

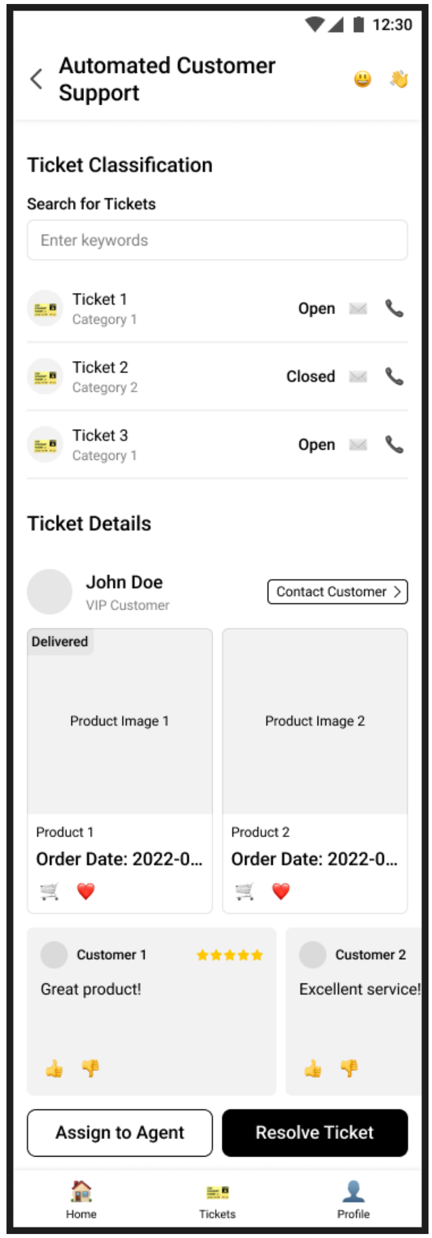
Data Acquisition Where will you source your data from? What is the cost to acquire these data? Are there any personally identifying information (PII) or data sensitivity issues you will need to overcome? Will data become available on an ongoing basis, or will you acquire a large batch of data that will need to be refreshed?	The company's existing support ticket database, which comprises historical ticket information, customer interactions, and issue resolutions, will be used to feed the automated customer support ticket categorization system. There will be no additional expense to get the data because it is already available within the company. To maintain customer confidentiality, data sensitivity, and personally-identifying information (PII) concerns must be handled by stringent data anonymization and privacy methods. As new support tickets are issued, the data will be regenerated regularly, ensuring that the ML model remains current and adjusts to changing customer demands and patterns for continued accuracy and efficiency.
Data Source Consider the size and source of your data; what biases are built into the data and how might the data be improved?	The quantity and source of the data, which comes from the company's current support ticket database, may contribute to biases, particularly in data categories/types that are under/overrepresented in the dataset. Certain sorts of concerns or client groups, for example, may be overrepresented, resulting in uneven classification. To address this, we will aggressively seek feedback from customers across various demographics to create a comprehensive and representative dataset, with a dataset size of roughly 100,000 support tickets. Data augmentation approaches will also be used to produce more balanced ticket samples. The system's performance will be evaluated regularly for bias-related issues, allowing for appropriate tweaks to the ML model and data-gathering method to ensure fair and unbiased ticket classifications.
Choice of Data Labels What labels did you decide to add to your data? And why did you decide on these labels versus any other option?	Labels added to data for automatic customer support ticket classification include support ticket categories including "Technical Issue," "Billing Inquiry," "Product Feedback," and "General Inquiry." These classifications were selected based on the most prevalent and repeating themes discovered in previous ticket data. The objective was to build a comprehensive collection of categories that effectively represent the many sorts of client inquiries that the support team faces daily. Using these precise labels, the ML model can reliably categorize incoming tickets into appropriate categories, allowing for efficient ticket routing and quick issue resolution, as well as useful insights into typical customer problems for proactive problem-solving.

Model

Model Building How will you resource building the model that you need? Will you outsource model training and/or hosting to an external platform, or will you build the model using an in-house team, and why?	The organization will consider outsourcing model training and hosting to an external platform or deploying an in-house staff to resource the automated customer service issue categorization model. The selection will be influenced by variables such as the company's skill in machine learning, available resources, and data security concerns. Outsourcing to an established ML platform may be a feasible option if the organization lacks in-house ML expertise or wants a speedy implementation. However, if the firm has talented data scientists and prioritizes data privacy, an in-house method might give more control over the model, better customization to unique needs, and a more effective way of dealing with data sensitivity concerns.
Evaluating Results Which model performance metrics are appropriate to measure the success of your model? What level of performance is required?	To test the performance of the automated customer support ticket classification model, several ML metrics such as accuracy, precision, recall, and F1-score will be used. Accuracy will assess the overall accuracy of ticket classifications, offering insight into the model's ability to detect ticket categories appropriately. Precision will be used to calculate the fraction of correctly categorized positive cases, which will indicate how effective the model is at categorizing certain ticket types. The recall, on the other hand, will evaluate the model's capacity to capture all affirmative cases, ensuring that no relevant ticket categories are missed. The F1 score will be used to create a compromise between precision and recall, providing an overall assessment of the model's efficacy. The model's performance will be measured by high values in these metrics, guaranteeing that the model consistently and efficiently classifies support requests, minimizing misclassifications, and improving customer support operations. The model will be fine-tuned and improved further through continuous monitoring and feedback.

Minimum Viable Product (MVP)

Design What does your minimum viable product look like? Include sketches of your product.	



Use Cases What persona are you designing for? Can you describe the major epic-level use cases your product addresses? How will users access this product?	As the persona, the automated customer support ticket categorization system primarily targets customer support agents. The most important epic-level use cases include efficient ticket categorization, faster response times, and improved issue resolution. When a support professional gets a customer ticket, they use a web-based user interface to access the system. The agent then enters the ticket text into the given form, allowing the system to quickly classify the ticket as a "Technical Issue" or "Billing Inquiry." This quick and accurate classification enables the agent to quickly route the ticket to the relevant support team, resulting in

	faster issue resolution and, ultimately, improved customer satisfaction. The go-to-market strategy includes the following fundamental components: identifying the target market, developing a convincing value proposition and product message, deciding the price strategy, and detailing the distribution plan.
Roll-out How will this be adopted? What does the go-to-market plan look like?	The automated customer support ticket classification system will be implemented by a well-defined go-to-market strategy. The strategy is divided into many stages, including internal testing and model improvement to assure accuracy and efficiency. Once the MVP has been confirmed, a pilot phase with a chosen set of support agents will be done to gather feedback and make required modifications. Following the successful trial, the technology will be gradually extended to all customer support teams, with agents receiving extensive training and assistance. To boost adoption across the enterprise, marketing activities will focus on emphasizing the system's benefits, such as speedier ticket routing and enhanced client experiences.

Post-MVP-Deployment

Designing for Longevity How might you improve your product in the long term? How might real-world data be different from the training data? How will your product learn from new data? How might you employ A/B testing to improve your product?	Long term, the product may be enhanced by collecting feedback from support agents and consumers regularly to discover areas for improvement. By supplementing the training data with real-world examples such as various client inquiries and emergent ticket categories, the model will become more resilient and responsive to changing consumer demands. Through periodic model retraining with the updated dataset, the product may learn from fresh data. A/B testing can be used to evaluate the effect of various model configurations or algorithm enhancements on performance. The system may determine the most effective model version for deployment by executing tests with subsets of support requests, leading to iterative improvements and optimal performance over time.
Monitor Bias How do you plan to monitor or mitigate unwanted bias in your model?	A thorough strategy will be used to detect and minimize undesired bias in the model. To begin, the team will carefully study the training data throughout the model construction phase to uncover any existing biases. To counteract these biases, strategies such as data augmentation, oversampling underrepresented groups, and applying fairness-aware learning algorithms will be

	adopted. The model's performance will be continuously checked after deployment to detect any bias-related concerns. A broad group of stakeholders will undertake regular evaluations to assess model fairness. If bias is found, the team will take remedial steps such as retraining the model with balanced data, improving the algorithm, or modifying the categorization categories to guarantee that all customer support complaints are treated fairly and equally by the system.