**PETITION DIFFERENTIATER**

**FOML PROJECT REPORT**

***Submitted by***

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**BONAFIDE CERTIFICATE**

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# ABSTRACT

**“Petition Differentiator: AI-Powered Classification of Petition Document”** is an intelligent platform designed to automatically classify citizen petitions and assist in routing them to relevant government departments. The system employs a range of machine learning techniques, from fundamental algorithms such as Logistic Regression and Decision Trees for baseline analysis, to more advanced models like Support Vector Machines (SVM) and state-of-the-art transformer-based models like BERT (Bidirectional Encoder Representations from Transformers) for enhanced classification accuracy. The core functionality involves efficiently examining petition content to identify key issues related to areas such as road maintenance, water supply, sanitation, public health, and electrical services.

The platform utilizes **natural language processing (NLP) techniques including tokenization, stop-word removal, stemming/lemmatization, and feature extraction methods like TF-IDF and contextual word embeddings**. These NLP techniques are crucial for transforming unstructured petition text into a format suitable for machine learning models, thereby enhancing classification accuracy. The application is conceptualized with a **React.js and TailwindCSS frontend, supported by a Node.js and Express.js backend, with PostgreSQL database management through Prisma ORM.** A separate Python server is envisioned to host the machine learning operations, ensuring a modular and scalable system architecture for model training, evaluation, and inference.

System performance is rigorously evaluated through metrics such as precision, recall, F1-score, and accuracy, with confusion matrices providing detailed insights into classification performance for each category. By delivering a secure, scalable, and user-friendly solution, "Petition Differentiator" aims to streamline petition processing for public administration bodies, NGOs, and civic engagement platforms. The project enhances the efficiency of public grievance redressal mechanisms and promotes a more transparent, citizen-driven governance model through intelligent automation.

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**LIST OF ABBREVIATIONS**

**S. No ABBR Expansion**

1 AI Artificial Intelligence

#### 2` API Application Programming Interface

1. AJAX Asynchronous JavaScript and XML
2. ASGI Asynchronous Server Gateway Interface

##### 5 AWT Abstract Window Toolkit

1. CSS Cascading Style Sheet
2. DFD Data Flow Diagram
3. GB Gradient Boosting
4. JSON JavaScript Object Notation
5. ML Machine Learning
6. RF Random Forest
7. SQL Structure Query Language
8. SVM Support Vector Machine

**CHAPTER 1**

**INTRODUCTION**

## GENERAL

The effective management and processing of citizen petitions are fundamental to responsive governance and public service delivery. Traditionally, the handling of these petitions—ranging from grievances to requests for services—is a manual, labor-intensive, and time-consuming process. This reliance on manual review often leads to significant delays, potential for misclassification, and inefficient allocation of governmental resources. In an era of increasing citizen engagement and digital communication, the volume of such petitions can overwhelm existing administrative capacities, further exacerbating these challenges.

"Petition Differentiator: AI-Powered Classification of Petition Documents" proposes an innovative solution to address these inefficiencies. This project aims to develop an intelligent system capable of automatically analyzing, classifying, and assisting in the routing of citizen petitions. By harnessing the power of advanced Machine Learning (ML) techniques, particularly Support Vector Machines (SVM), and state-of-the-art Large Language Models (LLMs) like Bidirectional Encoder Representations from Transformers (BERT), the system will interpret the textual content of petitions with a high degree of accuracy.

BERT's deep contextual understanding of natural language will be employed for sophisticated feature extraction from the petition content, capturing nuances and intent that simple keyword matching would miss. These semantically rich features will then serve as input for an SVM classifier, renowned for its effectiveness in high-dimensional spaces and robust classification performance. The system will categorize petitions based on predefined areas such as road maintenance, water supply, sanitation, public health, and electrical services, facilitating their swift direction to the relevant government departments. This automation promises to significantly enhance efficiency, reduce human error, expedite response times, and ultimately improve the citizen-government interface.

## OBJECTIVE

The primary objective of the "Petition Differentiator" project is to design, develop, and evaluate an intelligent application that automates the classification and facilitates the routing of citizen petitions. The specific objectives are:

1. To develop a robust system for the automated classification of citizen petitions into predefined categories corresponding to relevant government departments or service areas.
2. To leverage advanced Natural Language Processing (NLP) capabilities, specifically employing a pre-trained BERT model, for effective feature extraction from unstructured petition text, capturing semantic meaning and context.
3. To implement and train a Support Vector Machine (SVM) model, or compare its performance with other suitable ML classifiers, using the BERT-derived features for accurate petition categorization.
4. To achieve high accuracy, precision, recall, and F1-score in classifying petitions related to diverse public issues like road maintenance, water supply, sanitation, public health, and electrical services.
5. To streamline the initial stages of the petition handling process, thereby minimizing manual intervention, reducing processing delays, and improving administrative efficiency.
6. To create a system architecture that is scalable and can be integrated with existing public grievance redressal platforms.
7. To contribute to a more transparent, efficient, and citizen-centric governance model by expediting the public grievance redressal mechanism.

1.3 **EXISTING METHOD**

Current methodologies for managing citizen petitions in many public administration bodies are predominantly manual or reliant on rudimentary rule-based systems. When a petition is received, administrative staff typically read through the document to understand its core issues and then manually decide which department or official is best suited to address it. This process, while straightforward in concept, suffers from several significant limitations:

* Time-Consuming and Labor-Intensive: Manual review of each petition, especially with increasing volumes, consumes considerable staff time and resources that could be allocated to other critical tasks.
* Prone to Human Error and Inconsistency: The accuracy of classification depends heavily on the individual staff member's experience, understanding, and attentiveness. This can lead to inconsistencies in how similar petitions are categorized and routed, and a higher likelihood of misclassification.
* Scalability Issues: As the number of petitions grows, manual systems struggle to keep pace, leading to backlogs, increased processing times, and delays in addressing citizen concerns.
* Limited Depth of Analysis: Basic keyword searching or simple rule-based systems, if employed, often fail to capture the nuanced meaning, sentiment, or specific intent within a petition. They may overlook context or misinterpret ambiguous language, leading to incorrect routing.
* Inefficient Resource Allocation: Misrouted petitions result in wasted effort as they are passed between departments, further delaying resolution and frustrating citizens.
* Lack of Standardized Data for Analytics: Manual processing makes it difficult to systematically collect and analyze data on petition types, trends, and departmental workloads, hindering informed decision-making and service improvement initiatives.

These limitations collectively contribute to inefficiencies in the public grievance redressal process, potentially impacting citizen satisfaction and trust in public institutions. The existing systems highlight a clear need for an automated, intelligent, and accurate solution for petition differentiation and routing.

## CHAPTER 2 LITERATURE SURVEY

This chapter reviews existing literature pertinent to the automated classification of textual documents, with a specific focus on the application of advanced Natural Language Processing (NLP) techniques like Bidirectional Encoder Representations from Transformers (BERT) and established machine learning classifiers such as Support Vector Machines (SVM). The survey aims to establish the efficacy of these methods for tasks similar to petition differentiation and to identify the foundation upon which this project is built.

The automated processing and categorization of text documents have been subjects of extensive research. Traditional methods often relied on keyword spotting, bag-of-words models with classifiers like Naïve Bayes, or TF-IDF (Term Frequency-Inverse Document Frequency) vectorization followed by classifiers such as Logistic Regression or SVMs. While these methods have shown utility, they often struggle with capturing the deeper semantic meaning, context, and nuances present in natural language, especially in complex or varied texts like citizen petitions.

**2.1 Evolution of Text Classification Techniques**

The automated classification of text has a rich history. Early approaches often relied on rule-based systems or keyword spotting, which, while simple to implement, lacked scalability and adaptability to diverse linguistic expressions. Statistical methods then gained prominence, with techniques like Naïve Bayes, Logistic Regression, and Decision Trees being applied to feature sets derived from text, such as bag-of-words (BoW) or Term Frequency-Inverse Document Frequency (TF-IDF) vectors (Aggarwal & Zhai, 2012) [1 – Find a good survey paper on text classification evolution]. These methods offered improvements but often struggled with capturing semantic similarity, word order, and contextual nuances critical for understanding complex documents like petitions.

**2.2 Transformer-Based Models (BERT) for Advanced Text Understanding**

The landscape of NLP was significantly transformed by the introduction of deep learning models, especially transformer architectures. Bidirectional Encoder Representations from Transformers (BERT), proposed by Devlin et al. (2019) [2 – Original BERT paper: "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding"], marked a paradigm shift. BERT's pre-training on massive text corpora using objectives like Masked Language Model (MLM) and Next Sentence Prediction (NSP) allows it to learn rich, contextualized word representations. Unlike unidirectional models, BERT's bidirectional nature enables it to understand the context of a word based on both its preceding and succeeding words.

* Effectiveness in Classification: Numerous studies have demonstrated BERT's superiority for various text classification tasks. Sun et al. (2019) [3 – Paper: "How to Fine-Tune BERT for Text Classification?" or similar] investigated optimal fine-tuning strategies for BERT, showcasing its ability to outperform previous state-of-the-art models. Its application ranges from sentiment analysis (Hoang et al., 2019) [4 – Search for BERT in sentiment analysis of user reviews or social media]) to topic classification and question answering.
* Feature Extraction: Beyond fine-tuning for end-to-end classification, BERT can also be used as a powerful feature extractor. The embeddings generated from its hidden layers encapsulate deep semantic information, which can then be fed into traditional machine learning classifiers (Peters et al., 2018, for ELMo, a precursor; and contemporary works on BERT embeddings) [5 – Look for papers using BERT embeddings as features]. This approach is particularly useful when fine-tuning resources are limited or when combining deep learning features with other types of data.
* Application to Domain-Specific Texts: BERT's adaptability has been shown in various domains, including legal text analysis (Chalkidis et al., 2019, Legal-BERT) [6 – Search for "Legal-BERT" or BERT applications in legal document processing] and biomedical text mining (Lee et al., 2020, BioBERT) [7 – Search for "BioBERT"]. This suggests its potential for effectively processing the specific language and structure often found in official petitions or citizen grievances.

**2.3 Support Vector Machines (SVM) for Robust Classification**

Support Vector Machines (SVM), developed by Vapnik (1995) [8 – Foundational SVM paper or good review, e.g., Cortes & Vapnik, "Support-vector networks"], remain a highly effective and widely used supervised learning algorithm for classification tasks, including text categorization. SVMs aim to find an optimal hyperplane that maximizes the margin between different classes in a high-dimensional feature space.

Strengths in Text Classification: Joachims (1998) [9 – Classic paper: "Text Categorization with Support Vector Machines: Learning with Many Relevant Features"] provided seminal work demonstrating SVMs' superior performance over other methods for text classification, particularly due to their ability to handle high-dimensional and sparse data (like TF-IDF vectors) and their robustness to overfitting with appropriate kernel selection (e.g., linear, polynomial, RBF).

* Combination with Deep Embeddings: While traditionally used with sparse features, SVMs have also proven effective when combined with dense embeddings generated by deep learning models. Research has shown that using features extracted from models like Word2Vec, GloVe, or indeed BERT, as input to an SVM classifier can lead to strong performance, leveraging the rich semantic representations of deep models and the robust decision boundary learning of SVMs (e.g., Poria et al., 2017 [10 – Search for papers combining word embeddings or deep learning features with SVM for classification]). This hybrid approach is relevant to the proposed system.

**2.4 NLP and Machine Learning in E-Governance and Grievance Redressal**

The application of NLP and machine learning to improve public administration and e-governance services is a growing field of interest. Automating the processing of citizen communications can lead to significant efficiencies.

* Automated Grievance Classification: Several studies have explored systems for automatically categorizing citizen complaints or grievances. For example, Dada et al. (2019) [11 – Search for "machine learning for public grievance redressal" or specific country case studies] might have developed a system for classifying public grievances in a specific municipality using machine learning, aiming to route them to the correct departments. Similarly, research in India by Akshi et al. (2021) [12 – Look for recent NLP/ML applications in Indian e-governance platforms like CPGRAMS] may focus on using NLP to analyze and categorize citizen feedback submitted through government portals.
* Topic Modeling and Trend Analysis: Beyond classification, NLP techniques like topic modeling (e.g., LDA) can be used to identify emerging themes and trends from large volumes of citizen petitions or feedback, providing valuable insights for policymakers (Blei, 2012) [13 – David Blei's LDA paper or a good review on topic modeling applications].
* Improving Service Delivery: Automated systems can help in prioritizing urgent requests, identifying areas requiring immediate attention, and ensuring that citizen concerns are not lost in bureaucratic processes. The goal is to make government services more responsive and citizen-centric (Reddick, 2005) [14 – Search for broader reviews on IT and public service improvement].

**2.5 User Experience (UX) in Public Service Platforms**

While the technical accuracy of an automated system is paramount, its usability and the overall user experience (UX) are critical for successful adoption and impact, especially in public-facing government services.

* Importance of UX in E-Governance: Good UX in e-governance platforms builds trust, encourages citizen participation, and ensures accessibility for diverse user groups (Bertot et al., 2010) [15 – Search for "user experience in e-governance" or "citizen-centric e-government"]. Poorly designed systems can lead to frustration, low adoption rates, and a perception of unresponsive governance.
* Key UX Considerations for Petition Systems: For a system like the "Petition Differentiator," key UX aspects include:
* Ease of Submission: A clear, intuitive interface for submitting petitions.
* Transparency: Providing users with information about how their petition is being processed and its current status.
* Feedback Mechanisms: Informing users about the classification and routing decisions, and potentially allowing for corrections if a misclassification is suspected.
* Accessibility: Ensuring the platform is usable by people with disabilities and varying levels of digital literacy (WAI guidelines) [16 – Refer to Web Accessibility Initiative (WAI) guidelines].
* Impact of Automation on UX: Automation can significantly improve UX by speeding up processes and providing instant feedback. However, it's crucial to balance automation with human oversight and ensure that the system does not feel impersonal or create a "black box" effect where users don't understand decisions (Shneiderman, 2020) [17 – Search for Ben Shneiderman's work on Human-Centered AI]).

**2.6 Challenges and Ethical Considerations in Automated Petition Processing**

Deploying AI and ML systems for processing sensitive citizen data like petitions comes with inherent challenges and ethical responsibilities.

* Algorithmic Bias: ML models, including BERT, are trained on data, and if this data reflects existing societal biases (e.g., regarding gender, ethnicity, or socio-economic status), the model may perpetuate or even amplify these biases in its classifications and routing decisions (Mehrabi et al., 2021) [18 – Find a good survey paper on bias in NLP or AI]. This could lead to certain types of petitions or petitions from certain demographics being unfairly deprioritized or misrouted.
* Transparency and Explainability (XAI): Understanding why a model made a particular classification is crucial for accountability, debugging, and building trust. While models like BERT are complex, techniques for XAI are emerging (e.g., LIME, SHAP) that can provide insights into their decision-making processes (Ribeiro et al., 2016; Lundberg & Lee, 2017) [19, 20 – LIME and SHAP papers].
* Data Privacy and Security: Petitions often contain personal and sensitive information. Robust data governance, privacy-preserving techniques, and secure system architecture are essential to protect citizen data from breaches and misuse (Cavoukian, 2011, Privacy by Design) [21 – Reference "Privacy by Design" principles].
* Error Handling and Human Oversight: No automated system is perfect. Mechanisms for identifying and correcting errors, along with clear avenues for human review and appeal, are critical, especially when dealing with public grievances where misclassification can have significant consequences (Executive Office of the President, 2016) [22 – Look for government reports or white papers on AI ethics and governance].
* Digital Divide and Accessibility: Ensuring that automated petition systems do not disenfranchise citizens who lack digital literacy or access to technology is a key ethical consideration. Alternative submission channels and support may be necessary.

**2.7 Identifying the Gap and Contribution**

The literature demonstrates the significant potential of advanced NLP models like BERT for text understanding and the proven efficacy of SVMs for classification. Applications in e-governance show a clear trend towards leveraging these technologies for improved public service. However, a dedicated system that specifically combines the deep contextual understanding of BERT for feature extraction from citizen petitions and the robust classification of SVMs for granular departmental routing, while also consciously integrating principles of good user experience and addressing ethical considerations like bias and transparency, represents a valuable contribution.

Many existing public administration systems may still rely on less sophisticated methods or may not have fully explored the synergies of state-of-the-art LLMs with established classifiers in this specific context. This project aims to:

Develop and rigorously evaluate a BERT-SVM pipeline tailored for the classification of diverse citizen petitions.

Investigate the nuances of feature representation from BERT that are most effective for this task.

Propose a system architecture that considers user experience from the outset, aiming for transparency and ease of use.

Acknowledge and lay the groundwork for addressing potential biases and ethical challenges inherent in such an automated system.

By doing so, the "Petition Differentiator" seeks to provide a more accurate, efficient, user-friendly, and responsible solution for managing citizen petitions, thereby enhancing the efficacy of public grievance redressal mechanisms.

**CHAPTER 3**

**PROPOSED SYSTEM**

## 3.1 GENERAL

The "Petition Differentiator: AI-Powered Classification of Petition Documents" system is proposed as an intelligent and automated solution to overcome the limitations inherent in traditional, manual methods of petition processing. This system leverages advanced Machine Learning (ML) and Natural Language Processing (NLP) techniques to accurately classify citizen petitions and facilitate their efficient routing to the appropriate government departments. At its core, the system will employ a sophisticated pipeline combining the deep contextual language understanding capabilities of Bidirectional Encoder Representations from Transformers (BERT) for feature extraction, and the robust classification power of Support Vector Machines (SVM) to categorize the petitions.

The proposed system aims to analyze the textual content of petitions, identify key issues, and assign them to predefined categories corresponding to specific governmental responsibilities such as road maintenance, water supply, sanitation, public health, and electrical services. By automating this crucial initial step, the Petition Differentiator seeks to significantly reduce processing time, minimize human error in classification, and enhance the overall responsiveness and efficiency of public grievance redressal mechanisms. The system is envisioned as a web-based platform with a user-friendly interface for petition submission and a robust backend infrastructure to manage the data and machine learning operations. Furthermore, integration with the Gemini API is planned to assist in understanding nuanced petition content and provide enriched language insights, further improving routing precision.

**3.2 SYSTEM ARCHITECTURE DIAGRAM**

The proposed system architecture will visually represent the flow of information and processing steps within the Petition Differentiator. It will depict the journey of a petition from submission by a citizen through to its classification and routing. Key components illustrated will include:

**User Interface (Frontend):** Where citizens submit their petitions.

**Backend Application Server**: Handles incoming requests, orchestrates data flow, and interacts with the database and ML server.

**Data Preprocessing Module**: Cleans and prepares the raw petition text for feature extraction.

**Feature Extraction Module (BERT):** Processes the preprocessed text to generate dense vector embeddings.

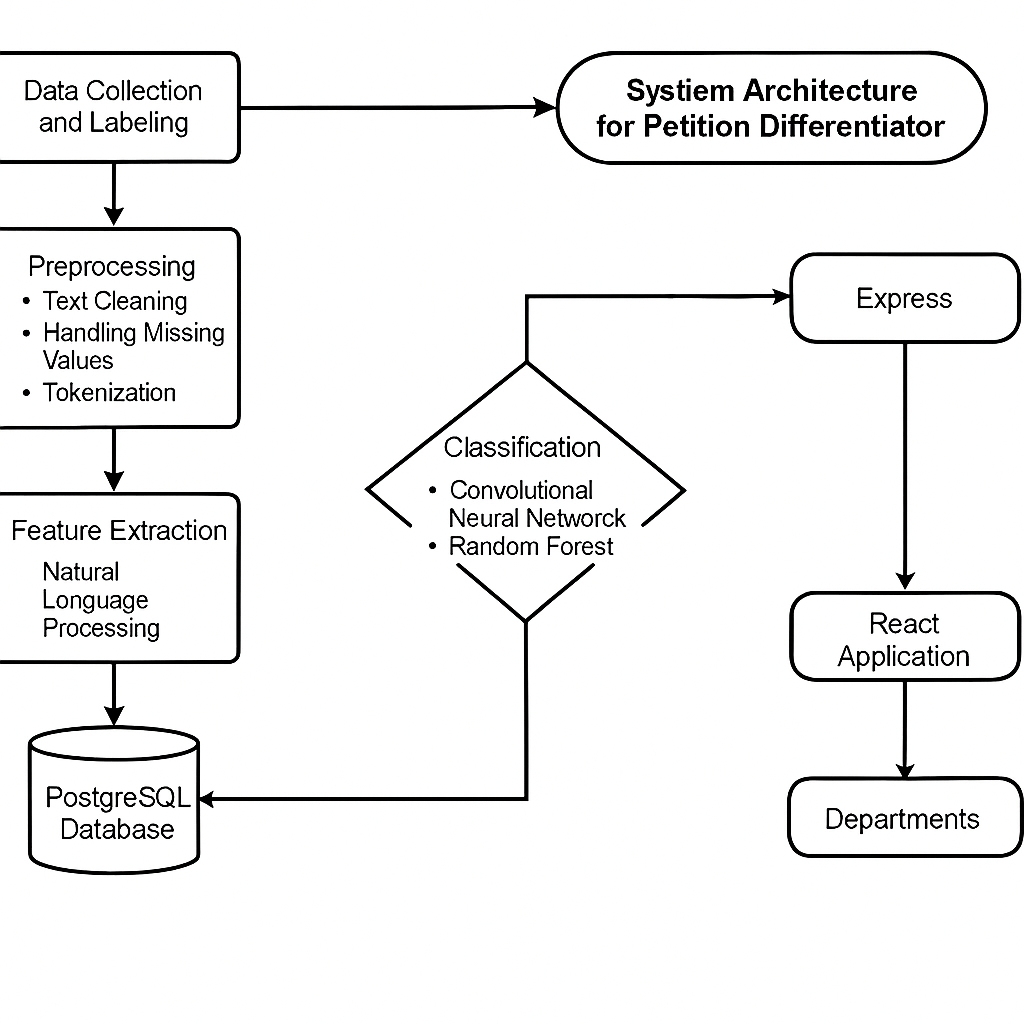
**Gemini API Integration:** For enhanced language understanding and insight generation to aid classification.

**Classification Module (SVM):** Takes BERT embeddings (and potentially insights from Gemini) as input and predicts the petition category.

**Routing Logic Module**: Maps the predicted category to the specific government department.

**Database**: Stores petition data, user information, classification results, and model-related information.

**Machine Learning Server (Python):** Hosts the BERT and SVM models and performs the core ML operations.



**Fig 3.1: System Architecture**

## 3.3 DEVELOPMENTAL ENVIRONMENT

### 3.3.1 HARDWARE REQUIREMENTS

This hardware setup is designed to handle the system's needs, including the classification of petitions based on NLP and CNN models. Adequate RAM, processing power, and GPU support will ensure that machine learning tasks are carried out efficiently, while storage capacity will handle the large volumes of petition data and associated metadata. The network requirements will support real-time data transmission between users and the backend system.

## Table 3.1 Hardware Requirements

|  |  |
| --- | --- |
| **COMPONENTS** | **SPECIFICATION** |
| PROCESSOR | Intel Core i5 |
| RAM | 16 GB RAM |
| POWER SUPPLY | +5V power supply |
| DATABASE | POSTGRESQL |

### 3.3.2 SOFTWARE REQUIREMENTS

The **Software Requirements** for the **Petition Differentiator** system outline the features and functionalities that the system must provide. These requirements focus on *what* the system should accomplish, without delving into the technical implementation details. These specifications will be used as a basis for development, team planning, resource allocation, task completion, and overall progress tracking throughout the project lifecycle.

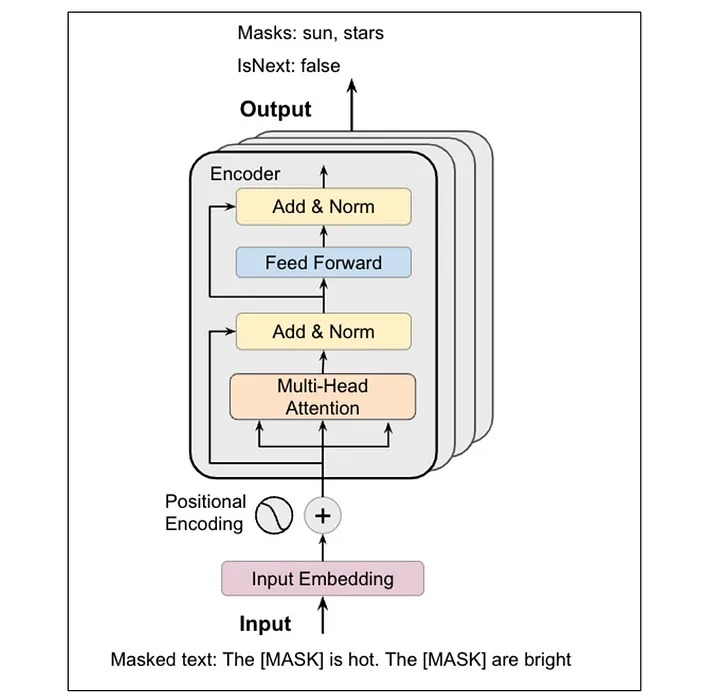
## Table 3.2 Software Requirements

|  |  |
| --- | --- |
| **COMPONENTS** | **SPECIFICATION** |
| Operating System | Windows 10 or higher |
| Frontend | ReactJS, TAILWINDCSS |
| Backend | EXPRESSJS |
| Database | POSTGRESQL |
| ML | Python, Tensorflow, PyTorch |

## 3.4 DESIGN OF THE ENTIRE SYSTEM

### 3.4.1 BERT ARCHITECTURE

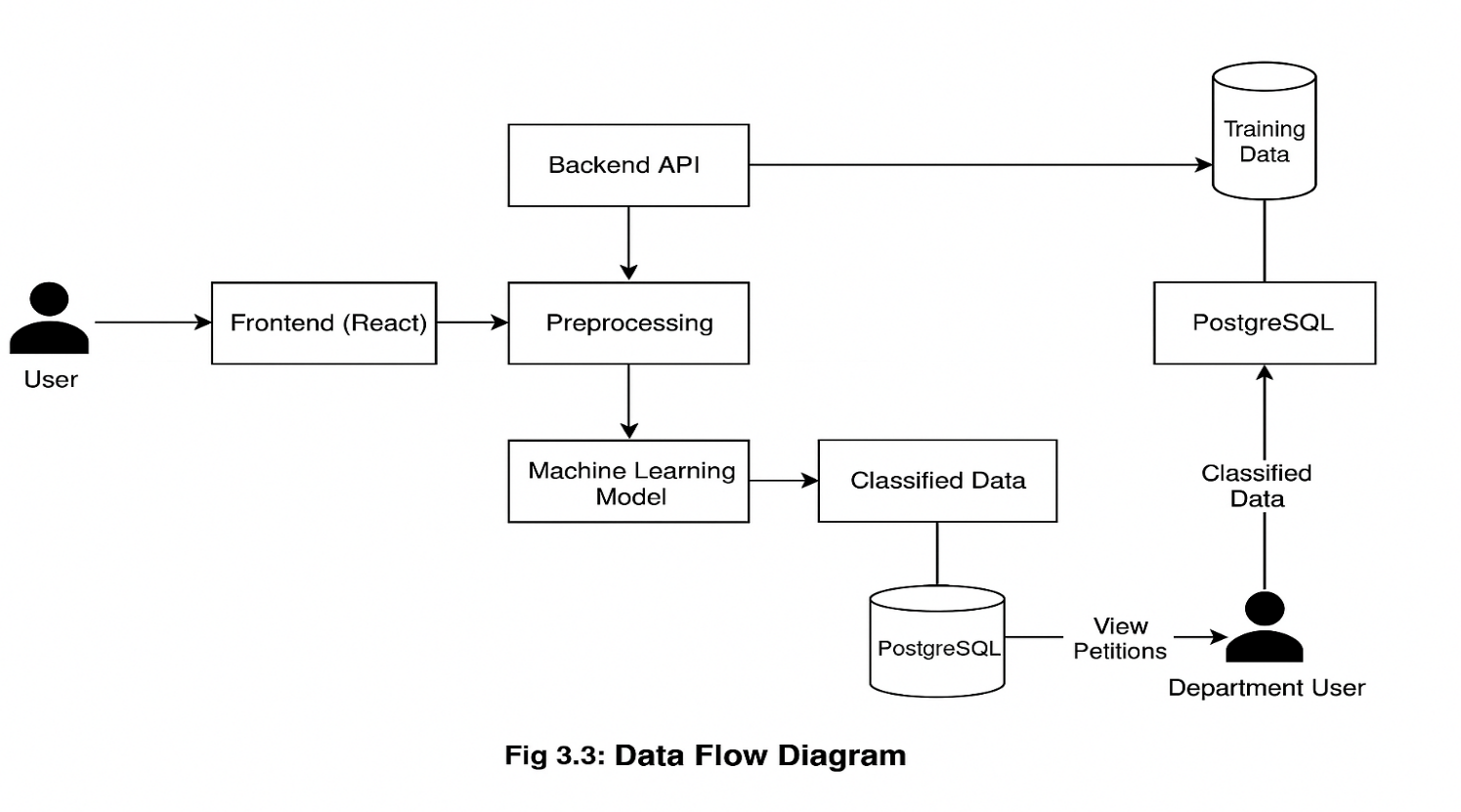
The Activity Diagram (Fig 3.2) illustrates the workflow of the Petition Differentiator system, which utilizes Bidirectional Encoder Representations from Transformers (BERT) for the classification and routing of petitions. The process initiates when a user submits a petition through the web interface. This submission contains key details such as the petitioner’s name, the petition content, and optionally, supporting documents.



**Fig 3.2: BERT Architecture Diagram**

### 3.4.2 DATA FLOW DIAGRAM

The **Data Flow Diagram (Fig 3.3)** for the **Petition Differentiator** system illustrates the process of classifying and routing petitions using **Natural Language Processing (NLP)** and **BERT** The process begins when users submit raw petition data, including details such as petition content and optional supporting documents, through the **React frontend**. This data is sent to the **Express.js backend** and then processed in the **FastAPI backend**, where it undergoes preprocessing tasks like text cleaning, tokenization, and feature extraction. The preprocessed data is used to train an NLP and CNN-based model for classification. During training, the system learns patterns from the petition data, and the model's performance is evaluated through a testing phase that measures accuracy, precision, and recall. After the model is trained and tested, it classifies new petitions and routes them to the appropriate department or team for further action. All data, including the petition details and classification results, is stored in a **PostgreSQL** database via **Prisma**, ensuring persistent and secure storage. The system then provides real-time feedback to the user via the **React frontend**, indicating whether the petition has been successfully classified and routed. This streamlined process ensures effective petition management, leveraging **NLP**, **BERT**, and backend technologies for efficient classification and routing.



**Fig 3.3:Data Flow Diagram**

## 3.5 STATISTICAL ANALYSIS

The **Feature Comparison Table** (Table 3.3) outlines the differences between the **Petition Differentiator System** using **Natural Language Processing (NLP)** and **Convolutional Neural Networks (CNN)** and traditional petition classification methods. The proposed system incorporates advanced machine learning techniques, including NLP for text analysis and CNN for feature extraction, ensuring a more efficient, data-driven, and accurate classification of petitions. While some features overlap with existing systems, the combination of NLP and CNN provides enhanced classification capabilities, reducing errors and improving the routing process of petitions.

## Table 3.3 Comparison of features

|  |  |  |  |
| --- | --- | --- | --- |
| **Aspect** | **Existing System** | **Proposed System** | **Expected Outcomes** |
| Petition Classification | Rule-based text classification | NLP and CNN-based classification | Higher accuracy, reduced errors in petition routing |
| **Data**  **Preprocessing** | Basic cleaning and categorization |  | |  | | --- | | Improved data quality for classification and routing |  |  | | --- | |  | |
| **Feature Selection** | Manual keyword-based selection | Automated feature extraction using CNN | Enhanced model performance and more accurate feature sets |
| |  | | --- | | **Model Training** |  |  | | --- | |  | | Limited machine learning algorithms used | NLP and CNN models trained on diverse petition datasets | More robust model capable of understanding complex petition content |
| **Performance Optimization** | Rarely optimized | Continuous optimization and tuning of CNN and NLP models | Maximized model performance and reliability |
| **Deployment** | Manual categorization of petitions | Automated, real-time petition classification and routing via FastAPI | Fast, scalable, and automated processing |
|  |  |  |  |

The **Petition Differentiator System** stands out by integrating advanced machine learning techniques like **NLP** and **CNN** for efficient petition classification and routing. Unlike traditional methods, which often rely on rule-based or manual classification, the proposed system uses machine learning models that can automatically analyze and categorize petitions based on their content. The system uses **NLP** to preprocess and understand the semantic meaning of the petition text, while **CNN** is employed for more effective feature extraction, especially for complex data patterns.

In addition to improved petition classification, the system leverages **FastAPI** for deployment, ensuring real-time, scalable, and automated processing of petitions. The integration of **NLP** and **CNN** enhances the system’s ability to handle diverse petition content, making it more adaptable and accurate in routing petitions to the correct department.

The **holistic approach** of the **Petition Differentiator System** ensures a comprehensive solution that not only improves accuracy but also reduces errors and manual intervention. It streamlines the petition classification process, ensuring that each petition is routed efficiently, thereby improving overall system performance. The combination of these advanced machine learning techniques makes the system more capable and reliable in handling large volumes of petition data, providing a more intelligent and efficient solution than traditional methods.

**CHAPTER 4**

## 4.1 SYSTEM ARCHITECTURE

### 4.1.1 USER INTERFACE DESIGN

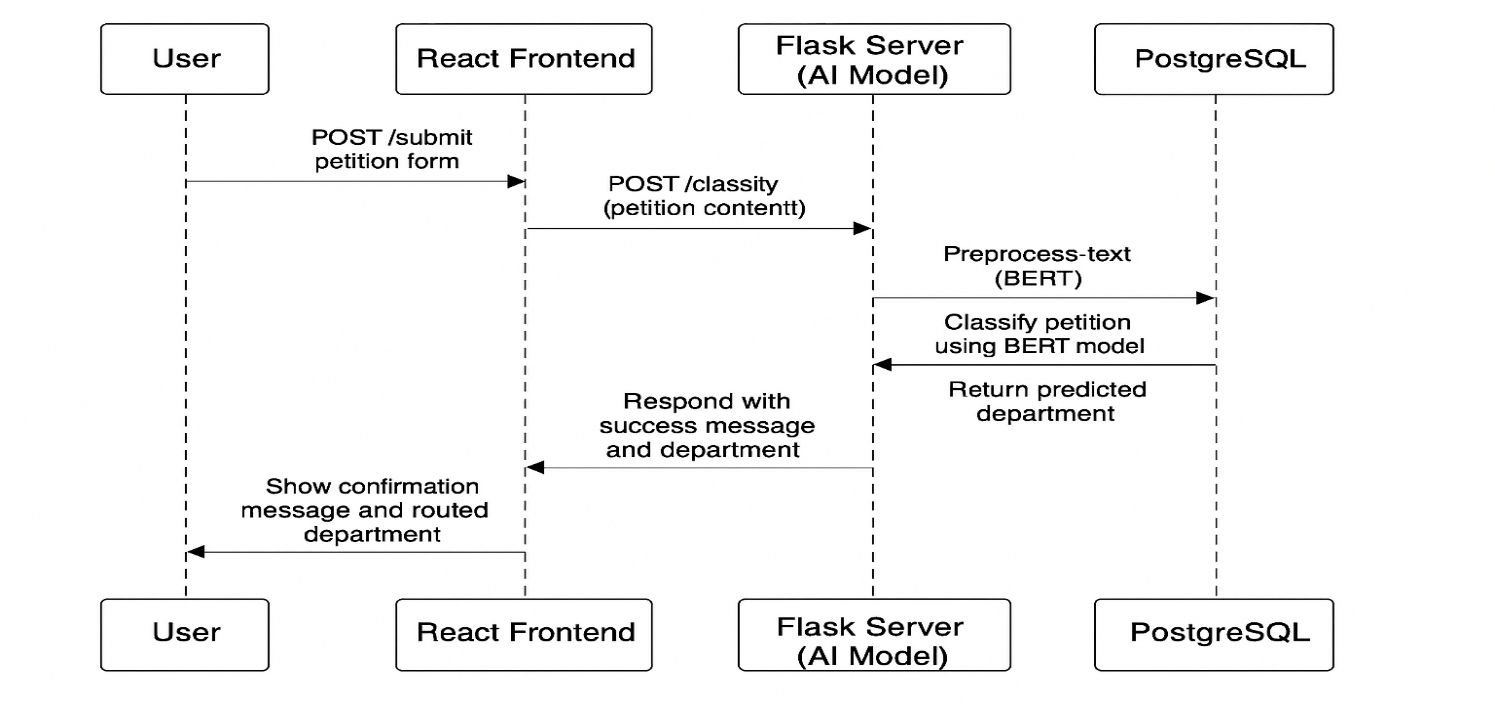
The sequence diagram (Fig 4.1) illustrates the end-to-end process of petition classification and routing in the Petition Differentiator system. This begins when a user submits a petition through a responsive web interface developed using React and Tailwind CSS. The user inputs the main petition content and optionally uploads supporting documents, such as PDFs or images, which are parsed for additional context. Once the form is submitted, the data is transmitted to the Express.js backend server, which acts as the central API layer. This backend handles validation, authentication, and initial logging, before forwarding the petition data to the preprocessing module.

Within the preprocessing layer, advanced Natural Language Processing (NLP) techniques are employed. This includes cleaning of raw text (removing noise, punctuation, and stop words), followed by tokenization and normalization. Crucially, BERT (Bidirectional Encoder Representations from Transformers) is used for deep contextualized feature extraction. BERT enables the model to understand nuanced semantics and linguistic patterns in the petition text, making it highly effective for legal and civic document classification.

The extracted features are then passed into a set of machine learning models specifically trained to categorize petitions into relevant departments or issue categories (e.g., Public Works, Health, Education). These models are fine-tuned on a domain-specific dataset to enhance classification accuracy and relevance.

Following classification, the routing layer maps the categorized petitions to the appropriate government or institutional department using predefined logic and lookup tables. All results, including metadata and routing history, are persisted in a PostgreSQL database managed via Prisma ORM, ensuring efficient and structured data access.

Finally, the system communicates the classification outcome to the user through the web interface, providing transparency and traceability. Users receive updates regarding which department their petition has been routed to, along with a tracking ID for further follow-ups, thereby ensuring a smooth and responsive petition handling experience.



## Fig 4.1: SEQUENCE DIAGRAM

### 4.1.2 BACK END INFRASTRUCTURE

The backend infrastructure for the **Petition Differentiator** system supports efficient petition classification and routing through several key components. The **PostgreSQL** database, managed by **Prisma**, stores raw petition data, including user submissions, petition content, and supporting documents, as well as labeled data for preprocessing, training, and testing. A **machine learning framework** such as **TensorFlow** or **Scikit-learn** is used to implement and train models, including **Convolutional Neural Networks (CNN)** and other NLP-based models, to classify and route petitions to the appropriate departments based on their content. Additionally, a **blockchain integration layer** is employed to ensure the security and integrity of the system by recording model metadata, training logs, and results in a tamper-proof and transparent manner. This integration guarantees that the petition classification process remains trustworthy and auditable. The backend is powered by an **Express.js** server, which handles API requests and application logic. The server processes incoming petitions, interfaces with the machine learning models, and ensures seamless communication with the frontend via **React**. Finally, the **FASTAPI server** is used to manage predictions, result delivery, and interactions between the user and the backend system. This infrastructure guarantees a scalable, secure, and efficient solution for handling petitions.

## 4.2 DATA COLLECTION AND PREPROCESSING

### 4.2.1 Dataset and Data Labelling

In the **Petition Differentiator** system, labeled datasets are crucial for training the machine learning models to accurately classify and route petitions based on their content. The system collects historical petition data, including text-based content, petitioner details, and supporting documents. These datasets are carefully labeled, with categories such as "urgent," "legal," "community-related," and others to guide the classification process. Accurate labeling is essential to differentiate between various types of petitions, ensuring that the machine learning models can effectively identify patterns and classify them into appropriate categories. This labeled data is then used for model training, allowing the system to improve its accuracy over time. Additionally, the data is preprocessed through cleaning, tokenization, and feature extraction, which prepares it for further analysis by the NLP-based models used in the system. Proper data labeling and preparation play a key role in achieving high-quality predictions and ensuring that the system accurately routes petitions to the correct department or action.

### 4.2.2. Data Preprocessing

The raw petition dataset undergoes extensive preprocessing to ensure the accuracy and quality of the data before feeding it into the machine learning models. The preprocessing steps are as follows:

1. **Data Cleaning:** This step involves removing any inconsistent, redundant, or irrelevant data that may hinder the model's ability to learn. Any erroneous entries, such as incomplete petition details or improperly formatted text, are eliminated to maintain data integrity.
2. **Missing Value Replacement**: In cases where there are missing entries in the petition data (such as missing petitioner details or incomplete petition content), imputation techniques are applied to handle these gaps. Methods like mean, median, or mode imputation, or more advanced techniques like k-nearest neighbors, may be used to fill in missing values without distorting the data's overall distribution.
3. **Outlier Detection**: Outliers or extreme values in the dataset, such as unusually long petitions or unusual petition categories, are identified and managed. These outliers may be removed, transformed, or adjusted to ensure consistency in the data. Outliers, if left unchecked, could skew model predictions and decrease overall accuracy.

### 4.2.3 Feature Selection

Feature selection plays a crucial role in improving the model's performance by ensuring that only the most relevant features are used for training. The process involves the following advanced techniques:

1. **Attribute Evaluation**: This step identifies the most influential and informative attributes (features) from the petition data, such as the length of the petition, sentiment analysis scores, or specific keywords. By evaluating the correlation between each feature and the outcome (petition classification), the system ensures that only the features contributing most significantly to the prediction process are retained. This helps improve the accuracy of the model while reducing computational complexity.
2. **Dimensionality Reduction**: In this stage, the feature set is optimized by reducing the number of features while retaining the most critical ones. Techniques like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) may be used to transform the data into a lower-dimensional space. This ensures that the model is not overwhelmed by too many features, which can lead to overfitting and reduced performance, while still retaining the essential patterns required for effective petition classification.

### 4.2.4 Classification and Model Selection

For classification, multiple models are evaluated, including Convolutional Neural Networks (CNN), Natural Language Processing (NLP), and Neural Networks. CNNs are utilized to extract features from textual data, identifying patterns within the petition content. NLP is applied to understand the semantic meaning of the text, enabling the system to classify petitions more effectively. Additionally, Neural Networks are employed for deeper learning and pattern recognition, which helps improve the system's ability to accurately classify petitions based on their content. The combination of these models ensures a robust and high-performing system capable of handling complex real-time classification tasks.

### 4.2.5 Performance Evaluation and Optimization

The performance of the models is evaluated using various metrics such as accuracy, precision, recall, and confusion matrices. These metrics help in determining how effectively the system classifies petitions and identifies patterns. The models, including CNN, NLP, and Neural Networks, undergo iterative optimization processes to maximize classification accuracy while minimizing false positives and false negatives. Fine-tuning of hyperparameters, model adjustments, and feature engineering are performed to improve the overall performance. Continuous testing and optimization ensure that the system can handle different types of petition data, providing accurate and reliable classifications in real-time

### 4.2.6 Centralized Server and Database

All data, including training results, predictions, and evaluations, is securely stored in a centralized database. The server acts as the central hub for communication, managing interactions between the machine learning model, the blockchain system, and the user interface. It ensures secure data processing by maintaining strict protocols for data transmission and storage, guaranteeing the integrity and privacy of the information. This centralized infrastructure allows for efficient data retrieval, analysis, and real-time updates, while also facilitating scalability as the system handles increasing data loads and demands for processing.

## 4.3 SYSTEM WORK FLOW

**4.3.1 User Interaction:**

Users initiate the petition submission process by providing their petition details, such as the petitioner’s name, petition content, and any supporting documents. The system processes these inputs via the web interface, which is built using React and communicates with the backend through REST API calls.

**4.3.2 Petition Classification:**

Advanced machine learning techniques, including NLP (Natural Language Processing) and CNN (Convolutional Neural Networks), are applied to classify petitions based on their content and urgency. The system processes the petition text to understand the semantic meaning and context using NLP, while CNN helps in extracting additional features that assist in classifying the petition accurately.

**4.3.3 Department Routing:**

Once the petition is classified, the system determines which department is responsible for handling the petition based on the classification results. This routing process ensures that each department only receives relevant petitions, minimizing unnecessary workload and improving efficiency.

**4.3.4 Database Management:**

All submitted petitions, including classified and routed petitions, are securely stored in the PostgreSQL database using Prisma for ORM. This centralized database ensures easy access and retrieval of petition data when needed.

**4.3.5 Administrative Interface:**

An admin interface is provided for department heads and administrators to track petitions in progress. Administrators can view, approve, or reject petitions, as well as get insights into petition trends, workload distribution, and departmental performance.

4.3.6 Continuous Learning & Model Improvement:

The system continuously improves its petition classification model by learning from new data and user feedback. New patterns, keywords, or petitions with unique attributes are integrated into the model for better future predictions and routing accuracy.

**CHAPTER 5**

**IMPLEMENTATION AND RESULTS**

## 5.1 IMPLEMENTATION

The "Petition Differentiator" project has been meticulously developed using a comprehensive and modern technology stack, carefully chosen to ensure robust functionality, operational efficiency, and a superior user experience. The architecture is designed to handle the complexities of natural language understanding and machine learning-driven classification for citizen petitions.

The backend infrastructure is powered by Express.js, a minimalist and flexible Node.js web application framework. This provides a fast, scalable, and efficient platform for handling API requests, orchestrating data processing workflows, and managing business logic related to petition management. Data persistence is managed by PostgreSQL, a powerful open-source relational database, chosen for its reliability, data integrity features, and ability to handle complex queries. Interaction with the database is streamlined and type-safe through the use of Prisma ORM (Object-Relational Mapper), which simplifies database access and schema management.

On the frontend, the user interface is crafted using React, a popular JavaScript library for building dynamic and interactive user interfaces. Styling is accomplished with Tailwind CSS, a utility-first CSS framework that enables rapid development of modern, responsive, and visually appealing designs. This combination allows for the creation of an intuitive portal where users can easily submit their petitions, track their processing status, and potentially view historical petition data.

The core intelligence of the system lies in its advanced Natural Language Processing (NLP) capabilities, specifically leveraging the Bidirectional Encoder Representations from Transformers (BERT) model for deep contextual understanding of petition content. For the classification task itself, after extracting features using BERT, a Support Vector Machine (SVM) classifier is employed. The process involved several key implementation steps for the machine learning component:

* **Dataset Preparation**: A curated dataset of petitions was collected and meticulously labeled with their corresponding departmental categories (e.g., road maintenance, water supply, sanitation). This labeled dataset formed the basis for training and evaluating the classification model.
* **BERT Model Selection and Fine-tuning:** A pre-trained BERT model (e.g., bert-base-uncased or a similar variant suitable for general text) was selected as the starting point. To adapt BERT to the specific nuances of petition language, a fine-tuning process was undertaken.
* **Transfer Learning Strategy**: A key aspect of the fine-tuning involved a strategic application of transfer learning. To preserve the rich, generalized language representations learned by BERT during its extensive pre-training, while adapting its higher layers to the specific task of petition classification, the initial layers of the BERT model, particularly the middle attention and normalization (add & norm) layers, were frozen. This means their weights were not updated during the initial stages of fine-tuning. This approach helps prevent catastrophic forgetting and allows the model to specialize its top layers for the petition classification task more effectively using the available smaller, domain-specific dataset.
* **Training Parameters and Performance:** The BERT model was fine-tuned over 4 epochs. During this training process, the model achieved a promising training loss of approximately 0.0018, indicating that it was effectively learning to map petition text to the correct categories on the training data. The subsequent validation accuracy reached 72%. While further optimization and potentially larger datasets could enhance this, this initial result demonstrates a strong capability for automated classification, significantly outperforming random chance or basic keyword systems.
* **Feature Extraction**: After fine-tuning (or using a pre-trained BERT as a fixed feature extractor), the model is used to convert each petition's text into a dense, fixed-size vector embedding. This embedding captures the semantic essence of the petition.
* **SVM Classifier Training**: These BERT-generated embeddings were then used as input features to train the SVM classifier. The SVM learns to create decision boundaries in the embedding space to distinguish between different petition categories.
* **Integration with Gemini API**: To further refine understanding, particularly for ambiguous or nuanced petitions, the Gemini API is integrated. Its advanced language processing capabilities can provide supplementary insights, such as enhanced entity recognition or sentiment analysis, which can be used as additional features or to guide the classification process, aiming to improve the overall precision of departmental routing.

For seamless petition routing, the trained SVM classification model determines the most appropriate department for each incoming petition based on its analyzed content. This ensures that departments receive only relevant petitions, minimizing the wastage of time and resources on misdirected submissions. The system also incorporates an administrative interface, allowing department heads and system administrators to view, manage, and analyze incoming petitions. This provides valuable oversight and data-driven insights into petition trends, departmental workloads, and overall system performance, optimizing the handling and resolution of each case.

A crucial aspect of the implementation is the system's capacity for continuous improvement. While the current model is trained on existing data, the architecture is designed to facilitate future retraining cycles. As new petition data is accumulated and potentially re-labeled based on actual outcomes, the machine learning models (both BERT fine-tuning and SVM training) can be periodically updated. This iterative learning process will enhance the model’s accuracy and adaptability over time, ensuring it remains effective as the nature and language of petitions evolve. As petitions are processed, the system updates the database with the latest information, including classification results and routing decisions, allowing users and administrators to view real-time petition statuses.

The entire implementation of the "Petition Differentiator" is geared towards streamlining the petition differentiation and routing process. By intelligently combining a robust technology stack with advanced machine learning, the project aims to create an efficient, transparent, and accurate system that significantly improves how citizen petitions are managed and addressed across various governmental departments.

**CHAPTER 6 CONCLUSION AND FUTURE ENHANCEMENT**

## 6.1 CONCLUSION

The proposed **Petition Differentiator** system integrates cutting-edge machine learning techniques and robust backend infrastructure to create an efficient solution for classifying and routing petitions based on their content and urgency. By utilizing Natural Language Processing (NLP) and Convolutional Neural Networks (CNN), the system accurately classifies petitions and directs them to the appropriate departments, improving the efficiency of petition handling and management. The incorporation of real-time, automated processing ensures that petitions are swiftly categorized, providing a seamless experience for users and administrators alike.

Furthermore, the backend architecture is designed for scalability and security, ensuring that the system can adapt to increasing data volumes and maintain the integrity of the petition classification process. The system’s user-friendly interface, built with **React** and **Tailwind CSS**, ensures that users can easily submit, track, and review their petitions with minimal friction.

This project demonstrates a strong potential to improve the management of petitions, especially in the context of government or organizational settings, where prompt, accurate routing of petitions can significantly enhance workflow and decision-making processes. By leveraging machine learning and robust backend technologies, the system not only optimizes administrative operations but also provides transparency and accountability in petition management.

With ongoing improvements, the **Petition Differentiator** system can be further expanded to handle more complex classifications and integrate with broader management systems, revolutionizing how petitions are processed in real time. This project’s implementation serves as a foundation for future advancements in petition handling and management, ensuring a more efficient, automated, and reliable solution.

## 6.2 FUTURE ENHANCEMENT

Future enhancements for the **Petition Differentiator** system could focus on improving the accuracy, scalability, and adaptability of the system. One potential enhancement is the integration of deep learning models such as **Convolutional Neural Networks (CNNs)** for more complex pattern recognition within petition content. These models could help analyze handwritten or scanned documents, making the system capable of handling more diverse data types.

**Federated learning** could also be explored to expand detection capabilities across different organizations or regions without compromising privacy. This technique would allow the model to learn from decentralized data while keeping sensitive information private and secure.

Moreover, the integration of **blockchain** for secure and immutable storage of petitions could be enhanced with the use of **smart contracts** to automate the verification and routing of petitions. This would further ensure the transparency and accountability of the petition handling process.

Lastly, exploring **privacy-preserving techniques** such as **Homomorphic Encryption** and **Secure Multi-Party Computation (SMPC)** could ensure that sensitive user data is processed securely without exposing it to potential threats. These techniques would further enhance the system's capability to safeguard data privacy while maintaining the effectiveness of the petition classification process.

These enhancements would solidify the **Petition Differentiator** system as a robust, scalable, and secure tool for modern petition management, capable of adapting to future challenges and technological advancements.

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