Smart Complaint System Using Generative-AI

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Abstract

The Smart Complaint System is a new means of modern civic maintenance, which is based on the use of artificial intelligence combined with the advanced web technologies to simplify the process of urban complaints submission and resolution. By simply attaching a photograph, citizens may report common problems that include potholes, garbage collections, damaged streetlights or water leakages. Installed as part of MERN architecture and backed by secure backend microservices, the platform offers personalised dashboards to users, authorities, and administrators, which ensures transparency and efficiency of operations. Automated processing, intelligent routing and real time tracking improves the experience of the user and provides departments with tools to track and respond to issues that are reported. Overall, this AI-based model is highly efficient when it comes to transforming reactive complaint management into inclusive, proactive, and scalable civic governance.

Keywords: Smart Complaint System, Artificial Intelligence, BLIP-2, MERN Stack, Vision-Language Model, Civic Maintenance, Urban Infrastructure, Complaint Automation, Smart Cities, Digital Governance

1. Introduction

Smart Complaint System is the system that is aimed at optimizing the processes of urban maintenance with the help of Artificial Intelligence (AI) and modern web technologies. People living in many municipalities face the same problems that include potholes, garbage piles, broken streetlights, and broken pipes, and often have no proper way to make a formal report. The platform mitigates this drawback by allowing the users to take a picture and upload it via a web interface. The AI model deployed (BLIP-2) reads the photo and recognizes the related issue and also grades the severity and the complaint is automatically sent to the respective governmental department. The platform is developed on the basis of MERN stack (MongoDB, Express.js, React.js, Node.js), and it provides three different functional modules: user, authority, and administrator. Users are able to make complaints and track their status; officials can view and amend the data of complaints; and supervisors handle the spatial information and departmental roles. All these characteristics make municipal governance more effective, transparent, and structured and, hence, make the city smarter and the quality of life of all stakeholders better.

2. Literature Survey

Rao, Patel, and Desai [1] proposed a complaint management system for the public sector that integrates BERT-based AI models to automate complaint clustering, classification, and routing. Their approach reduced the average response time significantly and improved departmental efficiency. The model also featured real-time dashboards and feedback loops to enhance transparency and citizen trust.

The IJARCCE team [2] developed CivicFix, an AI-based civic solution using cloud integration and microservices for smart complaint routing. Their architecture included user, authority, and admin modules with REST APIs and an automated email system. The system's smart routing engine accurately assigned complaints based on type and location, which reduced manual sorting time and improved resolution rates.

Zhang and Kim [3] discussed the application of multimodal Vision-Language Models (VLMs) like CLIP and GPT-4V to analyse urban images for safety and maintenance insights. Their model successfully detected civic anomalies such as damaged roads and poor lighting, demonstrating that vision-based machine learning can be used to monitor real-world infrastructure conditions with over 90% accuracy.

Civica [4] released an industry report detailing the use of AI in enhancing complaint workflows in local governments. Their solution used natural language processing (NLP) and AI-based classifiers to triage citizen complaints and assign them to appropriate departments. The system led to a 30% reduction in case backlog and increased user satisfaction by streamlining communication and status updates.

Springer authors [5] focused on explainable AI frameworks for civic applications, proposing strategies to make AI decisions interpretable in complaint management systems. Their work emphasized transparency, bias mitigation, and ethical oversight when AI is used in the public sector. They highlighted that integrating human-in-the-loop and explainability principles builds greater public trust and accountability.

3. Proposed Methodology

The Smart Complaint System architecture presented is a simple, performance-focused system that integrates the users with the AI-based processing, and government authorities, in a feedback loop. The interaction flow begins with a user taking a photo of a civic issue and sending the photo to a web application; at this point image is transferred to Appwrite, a cloud-hosted Backend-as-a-Service, and temporarily stored there. The material that was photographed is then directed to the AI microservice where the BLIP-2 model not only recognizes the type of the issue (e.g. pothole, garbage, broken light) and estimates its severity but also generates a complete complaint text using the Gemini AI language model. These AI outputs are consumed by the backend based on Node.js/Express.js that stores the data safely in MongoDB. Subsequently, the system will automatically forward the complaint to the relevant department, based on metadata obtained based on the identified classification and also on geographic coordinates, which have been embedded in the image. The authority gets an alert of the assignment and can view the complaint in an administrative dashboard, where the complaint can be moved through the stages of Pending, In Progress and Resolved. Instant emails are sent to the user in real-time, and they will allow a user to monitor the resolution process within the mobile application. There is an administrative module which offers supervision to assist in setting up of departments, spatial areas and user roles. Overall, such a close-knit paradigm makes the process of complaints resolution more swift, maintains a transparent communication process, and provides an easy to use interface to all stakeholders.

3.1. Proposed Model Diagram

The proposed system model of the Smart Complaint System shows how users, authorities, and admins interact through a unified platform. Users can easily submit complaints by uploading images and track the status of their complaints. Admins manage the system by adding or updating departments, places, and authorities. Once a user submits an image, it is processed by the AI model (using BLIP-2 through a FastAPI microservice), which analyses the image, identifies the issue, predicts its severity, and generates a suitable description. This processed information is handled by the backend, built on the MERN stack, which manages complaint records, sends email notifications, and securely stores data. Authorities then view and manage complaints relevant to their departments, updating their status as needed. Overall, the system connects all modules through REST APIs, allowing AI, backend services, and different user roles to work together seamlessly for faster and smarter civic issue resolution.

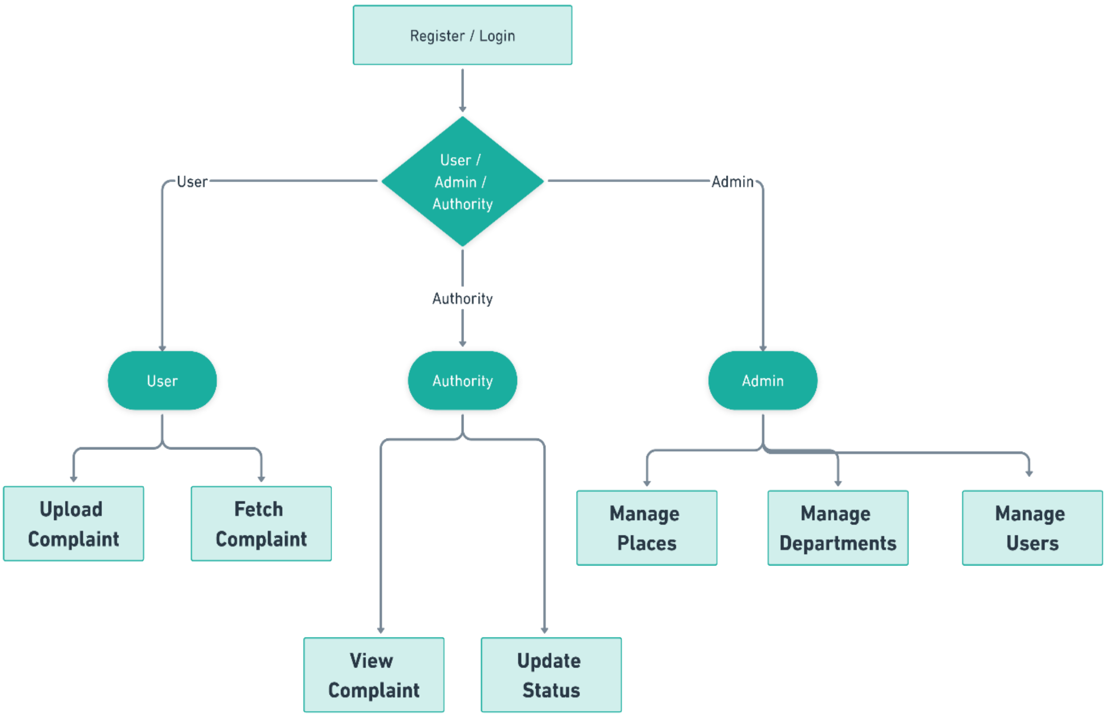

Figure 3.1.1 Block Diagram of Proposed System

3.2. Block Diagram of AI-Model

BLIP-2 is an AI model that can look at an image and describe it in words. First, it uses an image encoder to understand the picture. Then, a special part called the Q-Former helps translate the image information into a form that a language model can understand. Finally, a large language model (LLM) uses this information to generate meaningful text about the image, like a description or answer. In simple terms, BLIP-2 connects image understanding with language generation to explain images in natural sentences.

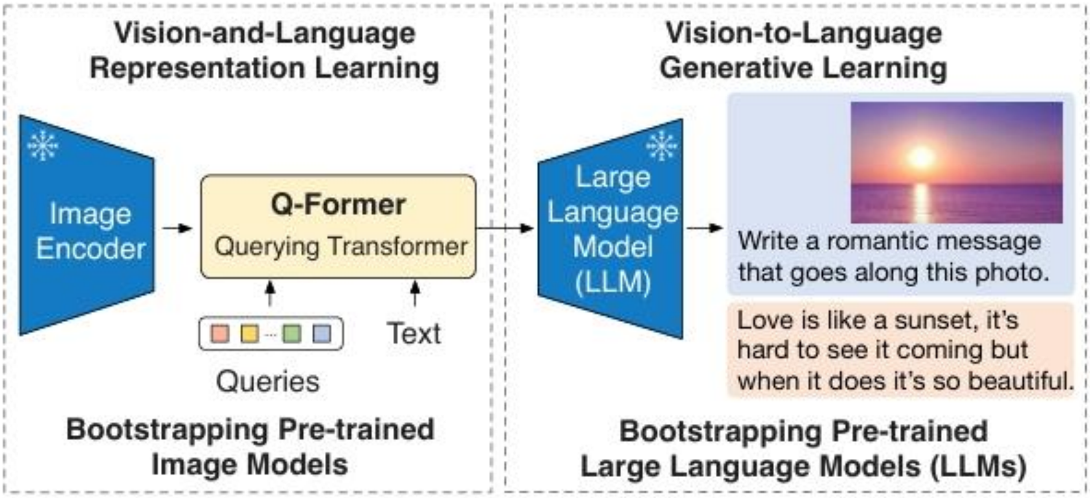

Figure 3.2.1 overview of BLIP-2 Framework

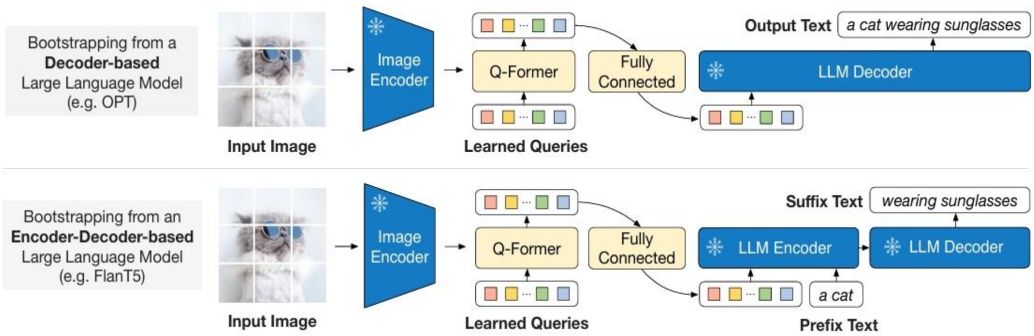

Figure 3.2.2 . BLIP-2's second-stage vision-to-language generative pre-training

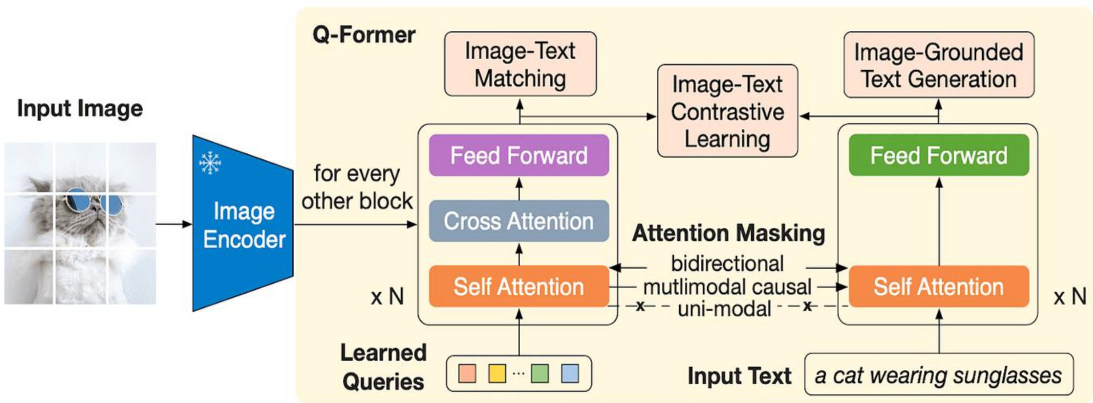

Figure 3.2.3 Model architecture of Q-Former and BLIP-2's first-stage vision-language representation learning objectives

4. Mathematical Formula

1. **Vision Encoding**

   The input image is converted into dense feature vectors using a Vision Transformer (ViT):

$$F_I = \mathrm{ViT}(I)$$

Where:

- I: Input image
- F_I: Patch-level image embeddings extracted using a pretrained ViT

2. **Q-Former Attention (Visual Relevance Extraction)**

   Query tokens attend to image features to extract meaningful visual context:

$$Q' = \mathrm{Attention}(Q, K = F_I, V = F_I)$$

Where:

- Q: Learned query tokens
- F_I: Image features (Key and Value)
- Q': Output query embeddings

3. **Language-Conditioned Scoring (Multiple-Choice Answering)**

   The model calculates similarity scores between each answer choice and the image-conditioned embedding:

$$\mathrm{Score}(a_i) = \mathrm{sim}(Q', \mathrm{Embed}(a_i))$$

Where:

- a_i: Answer option
- $\mathrm{Embed}(a_i)$: Textual embedding of the answer
- sim: Cosine similarity or dot product

4. **Softmax Over Choices (Probabilistic Output)**

   Softmax is used to compute the probability distribution over multiple choices:

$$P(a_i \mid I, Q) = \frac{\exp(\mathrm{Score}(a_i))}{\sum_j \exp(\mathrm{Score}(a_j))}$$

5. **Cross-Entropy Loss (Supervised Training)**
   The cross-entropy loss function is applied to optimize prediction toward the correct answer:

$$\mathcal{L}_{\mathrm{CE}} = -\log P(a_{\mathrm{true}} \mid I, Q)$$

Where:

- a_{true}: Correct answer label
- $P(a_{\mathrm{true}} \mid I, Q)$: Predicted probability for the correct answer

5. Results

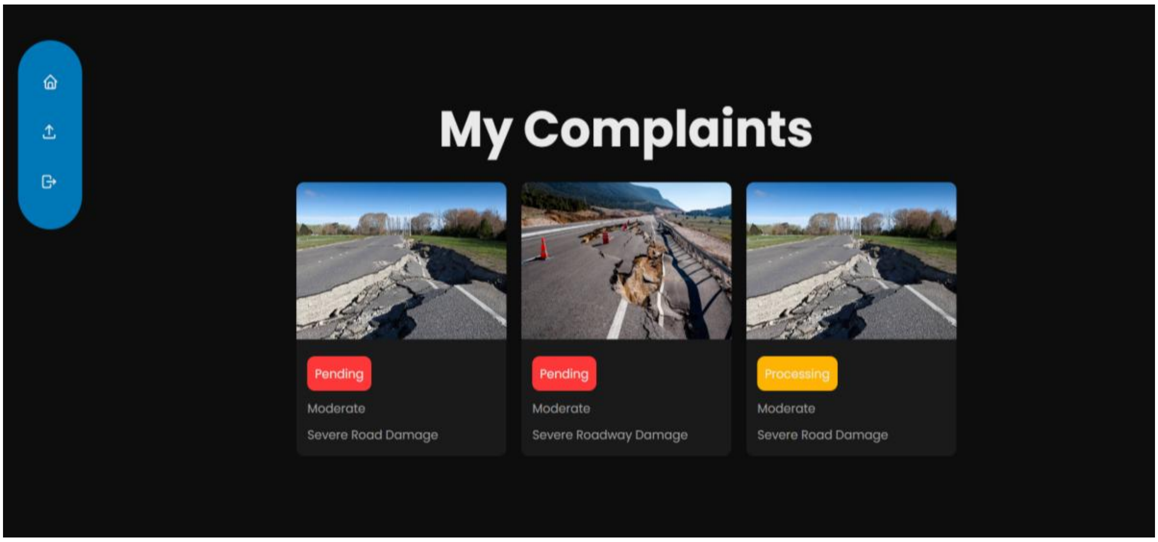

Figure 5.1 User Specific Complaint Page

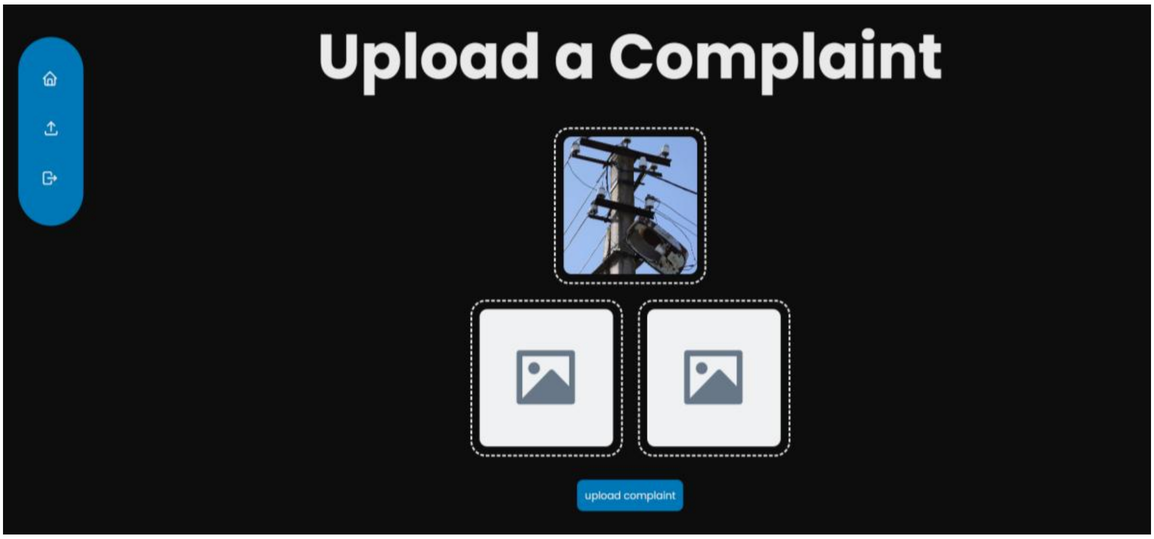

Figure 5.2 Upload Complaint Page

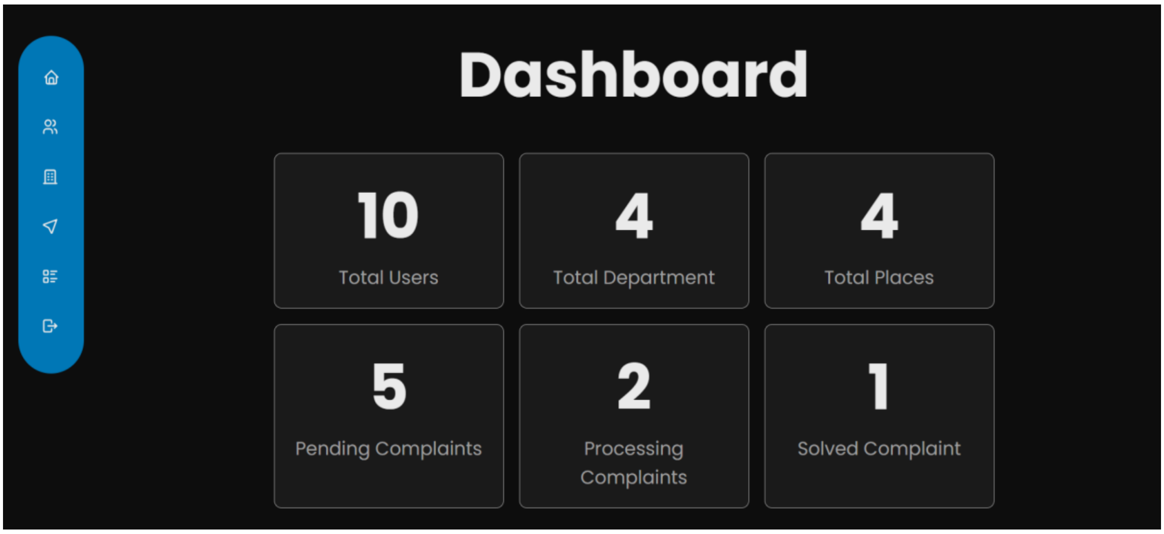

Figure 5.3 Admin Dashboard Page

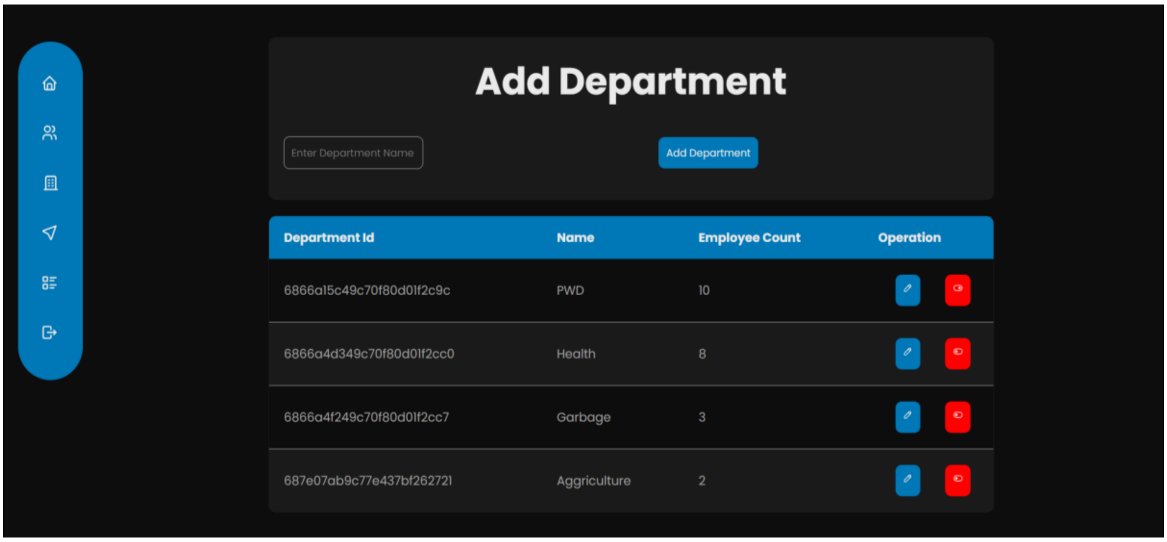

Figure 5.4 Add Department Page

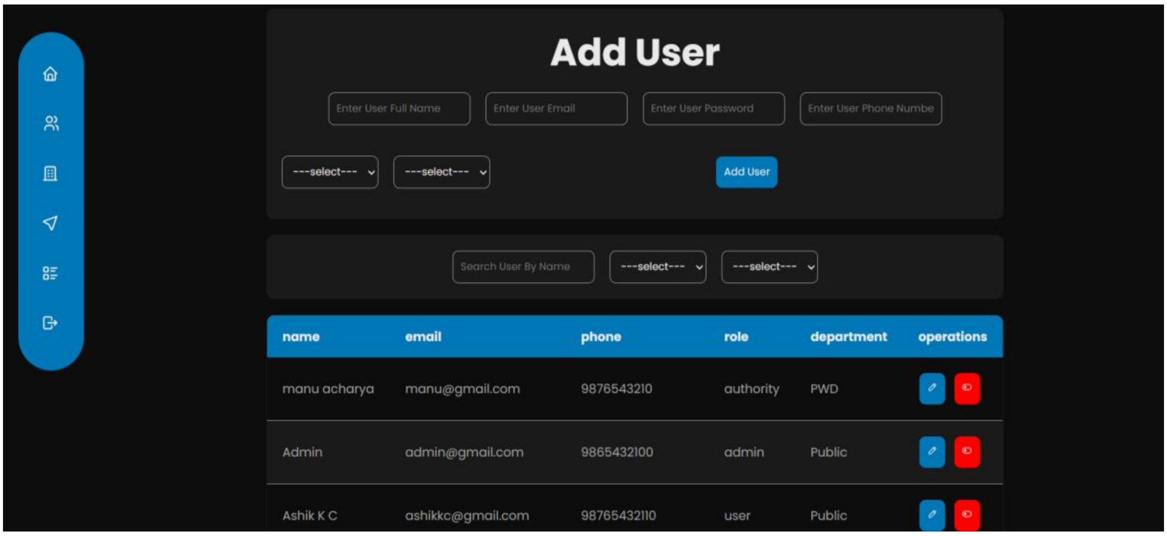

Figure 5.5 Add User Page

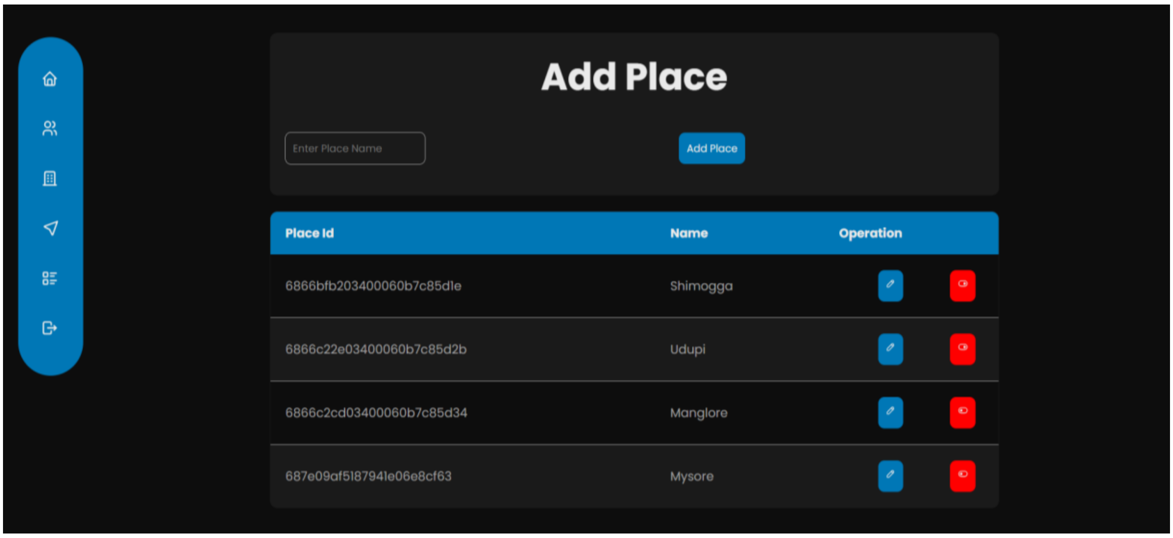

Figure 5.6 Login Page

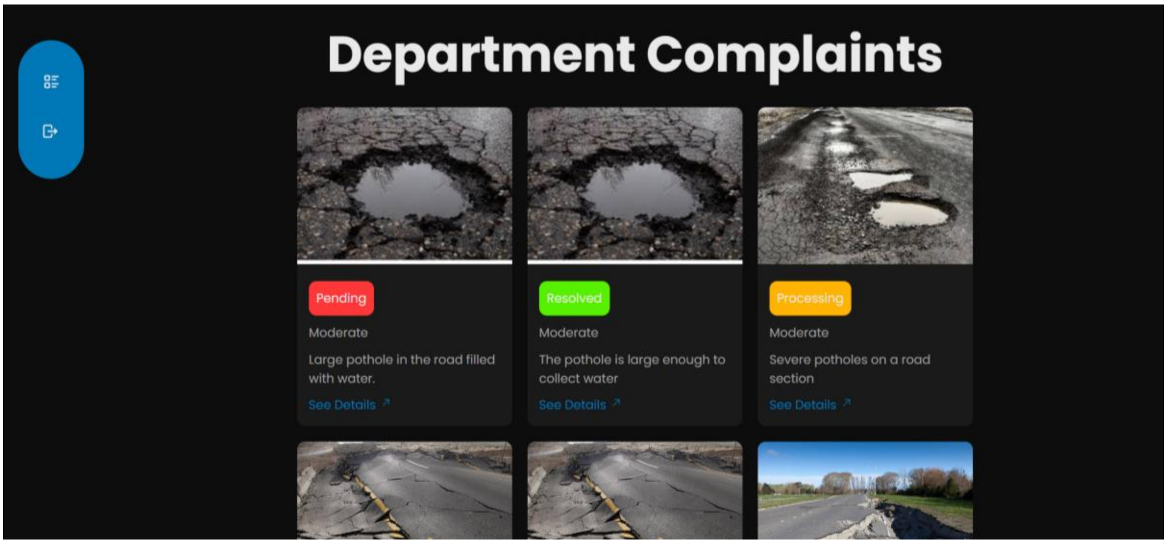

Figure 5.7 Department Specific Complaint Page

Conclusion

The Smart Complaint System is a new system of civic maintenance through artificial intelligence and automated processes. The system allows the citizens to file the complaints providing the photographs that are further processed according to the BLIP-2 model to recognize the type of the problem, its seriousness, and create the textual description. This process reduces the amount of manual work and speeds up the categorization of complaints. The structured complaints that ensue are then passed on to the relevant authorities so that they can make the necessary status updates immediately. The users can see the status of their complaints as they go along and are updated through email. Administrators are in charge of the location, department, and authority chains to provide smooth backend processes. The system is built on a scalable MERN stack core, with the interoperability to be used in different urban settings. Overall, the Smart Complaint System should be regarded as a significant element of interaction between citizens and civic authorities, thus helping to make cities cleaner, safer, and more efficient by means of enhanced reporting, tracking, and resolving of public matters.

Future Enhancement

To move Smart Complaint System to the next level of a next-generation civic platform, a number of innovative features will be proposed. To begin with, a multilingual complaint interface would significantly boost inclusivity as citizens with different linguistic backgrounds will find it easy to use the system. Second, using GPS data, a live heatmap and geo-analytics dashboard can be offered to administrators, so that high-density complaint zones could be viewed in real-time and smarter prioritization and faster response can be achieved. Third, AI-based prediction models could be trained using historical complaints associated with geolocation, enabling authorities to predict the areas that might be prone to recurring civic problems and preventative maintenance of the same. Fourth, there may be an emergency alert mode in which complaints that are in the vicinity of sensitive infrastructures (e.g. hospitals or schools) will automatically be marked to be handled on high priority. Fifth, it would be beneficial to integrate IoT-based real-time sensors to waste bins, water leaks or air quality, which would allow the system to automatically escalate complaints thus making it a proactive rather than a reactive framework. Lastly, in order to maintain a transparent and tamper-proof record keeping, blockchain technology may be used to record the complete lifecycle of each complaint, when it was submitted and when it was closed, thus establishing trust among the citizens and holding the various departments accountable

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