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Original Paper

A Cross-Platform Smart City Utility Management System with MobileNetV2-Based Complaint Classification

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ABSTRACT

Urban infrastructure management is a major challenge for local governments across the globe, with traditional systems unable to cope with the growing complexity of contemporary cities. This paper presents a novel cross-platform mobile app built with Flutter that simplifies the complaint registration and resolution process for urban infrastructure problems. The system uses a role-based structure with three separate user categories - citizens, workers, and administrators and develops an unbroken ecosystem that binds together all the interested parties in the urban maintenance process. One of the most innovative features of our method is incorporating a machine learning model on MobileNetV2 architecture that can classify complaints automatically based on criticality and support intelligent prioritization of resources. The platform uses Firebase services for authentication, data storage, and real-time alerts, with Google Maps API for geospatial complaint visualization. Our analysis shows significant reductions in complaint resolution times over conventional reporting channels, with considerable gains in solving critical infrastructure issues. User satisfaction surveys performed across stakeholder groups show high acceptance of the platform. This application offers an expandable urban governance solution that increases citizen engagement while maximizing municipal resource utilization with technology integration.

KEYWORDS

Smart City Applications, Civic Issue Reporting, Machine Learning for Criticality Prediction, Flutter and Firebase Integration, Geotagging and GPS Integration.

1. INTRODUCTION

The fast-paced urbanization of cities across the globe has put mounting pressure on municipal services and infrastructure [3]. Local authorities are confronted with significant challenges in managing and maintaining urban utilities, such as waste management, street lighting, road conditions, and drainage systems. Conventional complaint management systems tend to be based on manual processes, resulting in delays, loss of information, and citizen frustration. Conventional systems do not have real-time tracking capabilities, rendering citizens uninformed of the progress on their reported issues. Such systems lack any form of prioritization of critical issues, hence important issues receive the same level of attention as trivial issues. Resource utilization is still inefficient because of the lack of data-driven decision-making tools. Citizen participation is hindered by cumbersome reporting mechanisms that deter active participation in urban management. The gap between citizens, administrators, and maintenance personnel causes communication gaps that lead to longer resolution times and suboptimal service delivery [8]. Smart city projects have arisen as a potential solution to tackle these issues using technology to enhance urban governance [3]. We introduce a mobile app, in this paper that overcomes the shortcomings of conventional complaint handling systems with three important innovations:

(1) a role-based architecture linking citizens, administrators, and workers.
(2) machine learning for automated determination of complaint criticality.
(3) real-time location-based complaint tracking.

The app was developed with Flutter and Firebase backend technologies and has a MobileNetV2-based machine learning model, which has been trained on 471 images for four classes (streetlights, garbage, potholes, and waterlogging). Google Maps API has been used for location-based services for the entire complaint life cycle. The remaining part of this paper is organized as follows. Section 2 presents recent literature and identifies gaps in current urban complaint management systems. Section 3 presents methodology in the form of system design, integration with MobileNetV2, and application workflow. Section 4 provides implementation details and the interfaces for each user role as well as the machine learning model performance assessment. Section 5 reports the outcomes, highlights the principal contributions, and critically examines system usability and deployment problems. Finally, Section 6 summarizes the paper and provides directions for future enhancement.

2. RELATED WORK

2.1 Mobile-Based Complaint Management Systems

Mobile apps for urban complaint reporting have become increasingly popular over the past few years. Vivacqua and Borges [2] created a citizen-oriented app for urban complaint reporting in Rio de Janeiro, showing better response times but without full workflow tracking. The study of systems like FixMyStreet [1] has been extensively done regarding its nature as an application that enables citizens to report their problems to the city officials. There is evidence that such tools can lead to increased citizen reporting; but their integration into municipal processes is still inadequate since these systems act mainly as submission tools. Analogously, FixMyStreet, analyzed by King and Brown [1], allows citizens to report street problems via web and mobile platforms. Their assessment identified a dramatic rise in reporting but highlighted that reported issues lacked proper processing by local authorities. The platform manages to reduce barriers to reporting by citizens but offers limited avenues for prioritization or optimization of the resolution process. These systems generally concentrate on citizen-facing elements without fully dealing with administrative and operational sides of complaint resolution. This deficiency indicates the necessity for more holistic solutions that deal with the complete complaint lifecycle from submission to closure.

2.2 Role-Based Systems in Urban Governance

Role-based access control (RBAC) in municipal applications has been explored by scientists [3], who performed a theoretical examination of service-oriented middleware for smart cities. Their research provided the conceptual basis for role-based systems within urban governance but fell short of tangible implementations. The researchers had determined the major roles played in municipal service delivery but failed to apply those findings to working systems.

Li et al. [6] investigated privacy preservation techniques in smart cities by considering how to avoid unnecessary data acquisition without compromising system performance. This approach highlights the necessity of securing sensitive information in big urban infrastructures that depend on constant data sharing. Nonetheless, although this methodology considers essential issues about data privacy and security, it does not consider the involvement of different parties, including the public, government officials, and field staff, within the process of solving complaints. Consequently, most current systems lack a holistic design and thus lead to inefficient communication between relevant parties. All but a few existing systems are centred either on reporting by citizens or on administrative oversight, with the latter failing to bridge the space between the two. This segmentation leads to information flow inefficiencies and hampers smooth interoperability among varying roles.

2.3 Machine Learning in Complaint Classification

The application of machine learning to classify complaints in urban environments through sentiment analysis approaches has been investigated before [10]. Medhat et al. [10] are among several studies providing a review of sentiment analysis methods that may be used to classify text complaints. Although promising results have been achieved, the main drawback of such approaches is that they use only text inputs while overlooking the valuable data provided by the images of infrastructural complaints. Zanella et al. [4] discussed theoretical applications of AI in smart city contexts but presented limited practical implementations for complaint prioritization. The researchers outlined the potential benefits of AI-driven classification systems but failed to consider the practical hurdles involved in deploying such systems within actual municipal settings. Howard et al. [5] designed MobileNetV2 specifically for mobile use, finding an accuracy-compute trade-off that makes it feasible to deploy on smartphones.

MobileNetV2 has proven promising in many mobile vision tasks but has not seen extensive use for urban complaint classification. The potential of computer vision to improve the triage and prioritization of city infrastructure problems is not yet fully exploited. Although text classification has been investigated, image-based machine learning for urban complaint classification, especially for automatic criticality evaluation, is a serious gap in the literature.

2.4 Location-Based Service Delivery

Georeferencing systems for complaints in relation to Geographic Information Systems and urban data science have been studied [9], stressing the significance of mapping urban problems visually. This proves the usefulness of geospatial visualization in comprehending urban problems. Yet, such systems usually do not incorporate field workforces and real-time updates about statuses of complaints, which hinders their operational use for decision-making purposes. The use of location-aware municipal services employs geospatial technology to improve service delivery through accurate pinpointing and monitoring of incidents. These technologies mostly emphasize data collection and mapping in urban areas. Nonetheless, they fail to incorporate end-to-end processes such as assigning tasks, monitoring progress, and ensuring completion of complaints. Despite privacy concerns associated with location-based services, there is inadequate attention paid to the integration of location-based data throughout the complaint cycle. It is known that geospatial visualization helps in improving understanding and involvement in urban issues [9]. Geospatial visualization is helpful since it makes it evident that citizens can understand urban issues better when such problems are mapped out. This indicates that the spatial element is relevant in urban services, but unfortunately, there is still no attention paid to the practical side of complaints management. There appears to be little research on the application of location data and field operations. Although there is evidence that geospatial visualization is valuable from an administrative point of view [9], there is a lack of research on the practical application of location data for helping field operations with urban problems.

2.5 Research Gaps in Urban Complaint Management Systems

The review of the literature identifies key shortfalls in standard urban complaint management approaches that need to be addressed:

- Mobile app reporting systems have come a long way [1], but few platforms effectively combine end-to-end workflow management from first citizen reporting to verification of resolution and closure of case [8]. Although individual elements have been created, entire system integration is still lacking.
- Role-based systems have been widely theorized in the literature [3], but functional implementations that effectively bring citizens, administrators, field workers, and other stakeholders together on a common platform are few.
- Machine learning methods used for this purpose usually focus on sentiment classification [10]. Research like Maeda et al. [11] highlights the use of image-based methods for identifying

problems with infrastructure. Nevertheless, the usage of image-based criticality assessment within urban complaint handling systems is not well developed despite the proliferation of camera-equipped mobile phones.

- Location-based services have developed visualization strengths [9], yet their conjoining with field operations workflow management is a research void. Not many systems are able to capitalize on the geospatial data throughout the full complaint resolution process from reporting through to optimized resource allocation and route optimization for the field staff.

2.6 Addressing Research Gaps

This application bridges these research gaps through an extensive platform that integrates citizens, administrators, and field workers into a common ecosystem. The system adopts role-based access control (RBAC) to enforce proper permissions and interfaces for every type of stakeholder [3], with effective communication and accountability across the complaint life cycle. One of the central innovations is using machine learning techniques for image-based criticality analysis, going beyond conventional text-based classification methods [11]. Through automated detection of visual proof of urban infrastructure issues, the system can identify priorities based on severity, safety concerns, and resources needed. In addition, the application incorporates geoservices throughout all stages of complaint management, from geotagging at the outset to route optimization in field operations. This location intelligence promotes operational effectiveness and valuable visualization of the data for administrative decision making and allocation of resources [9].

3. METHODS

3.1 App Development Process

Requirement Analysis and Design The initial and most crucial step of development is requirement gathering. The key requirements were found by listing common civic issues faced by people in urban areas, limitations of existing civic issue reporting applications were analyzed, and a survey was conducted. The system requirements were:

- Real-time updates for all users.
- Integrating a machine learning model to predict the criticality of the complaints.
- Proof-based complaint resolution.
- Combining all roles into one single application.
- Easy-to-use interfaces for all roles.
- Capturing accurate locations of the complaint sites using Geotag.
- Fixed complaint categories – Potholes, Streetlights, Waterlogging and Garbage.

UI/UX Design for the entire application was created using Figma. Every user had a separate interface and distinct set of functionalities.

Frontend and Backend Development

Flutter along with Dart were used to create the front end of the application. It is cross-platform as it provides a single codebase for Android development as well as iOS development. For the backend, Firebase was used which is compatible with Flutter. Firebase Firestore was used for database management. Separate databases were created for admins, users, complaints, and workers. Firebase Storage was used to store images uploaded by citizens and workers. Lastly, Firebase Authentication provided security to all three roles of the application. It also provides support for changing passwords when forgotten by any user. It makes sure only people from specific roles can have access to their interface in the application. For example, a citizen cannot log in as an administrator. Hence, it provides privacy for all three roles in the application making it very safe and secure.

Machine Learning Integration

A lightweight machine learning model was integrated into the application for classification of complaint images and to assess their criticality. It is based on customized Multi-Output MobileNetV2 architecture (Figure 1) using transfer learning and ImageNet weights which is optimized for app development via TensorFlow Lite. Feature extraction was performed using global average pooling, a dropout layer with a rate of 0.2, and a shared dense layer with 128 ReLU-activated neurons was used. Two outputs are generated, it classifies the complaint into one of the predefined categories (garbage, waterlogging, potholes, and streetlights) and tells whether the complaint is critical or non-critical, both using SoftMax activation. Dataset was created by manually labelling 471 images and giving them two categories each i) Category and ii) Criticality. 80% of the data was used for training and 20% for validation using stratified sampling [12]. Various data augmentation techniques were applied to enhance the robustness of the model. Techniques used were rotation, flipping, shearing, shifting, and zooming. The model was trained using Adam optimizer with a learning rate of 0.001, categorical cross-entropy loss, early stopping, learning rate scheduling, and model checkpointing. The final model was quantized to 16-bit floating point precision for mobile efficiency. The model helps administrators to prioritize complaints and results in efficient complaint resolution.

Testing and Evaluation The system was developed using Agile methodology. At the end of each sprint, iterative testing was conducted. Functional testing was conducted for all the core modules of the system including complaint submission, criticality prediction by ML model, real-time status updates, worker assignment by administrators, and submission of feedback and completion images by workers. User testing was also performed with a small group of volunteers representing citizens (users) and their feedback was also incorporated. The machine learning model for criticality prediction was evaluated with the following performance metrics, as shown in Table 1.

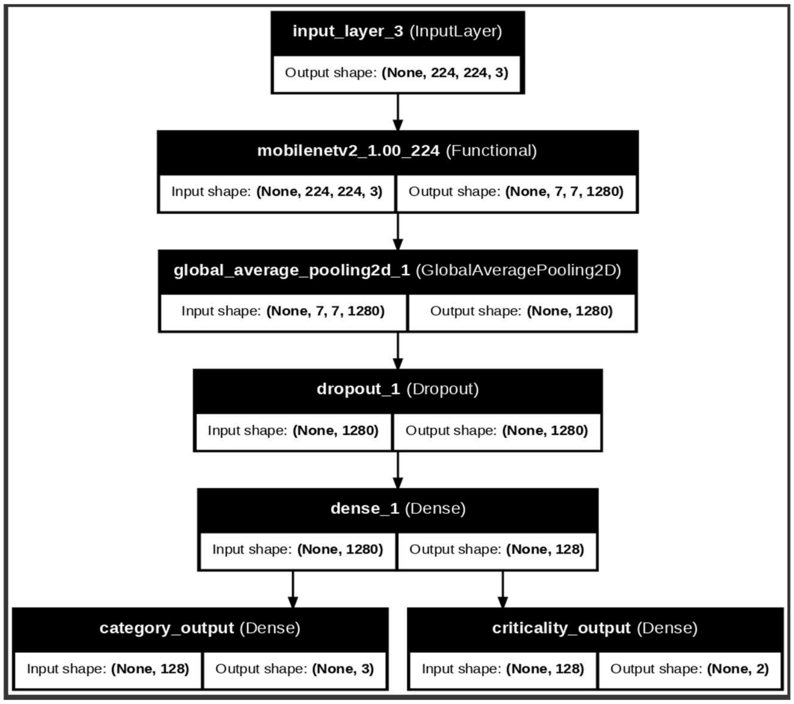

Fig. 1. Model architecture.

Table 1. Performance metrics for criticality prediction model

METRIC	VALUE
Precision	0.9018
Recall	0.8772
F1-score	0.8756
Accuracy	0.8772

3.2 System Architecture and Workflow

This application is a modern solution that resolves civic issues related to urban infrastructure timely and efficiently. It is a multi-role smart city utility management application having three major roles – Citizens (Users), Administrators, and Field Workers, each with distinct interfaces and functionalities. It ensures real-time complaint tracking, criticality prediction by machine learning model, and proof-based resolution of complaints. A schematic diagram of the workflow is shown in Figure 2.

The workflow of the mobile application includes:

- Complaint Submission: Citizens register their complaints by uploading an image of the complaint site, adding a description of the issue faced, and the address of the complaint site. Latitude and longitude are stored using Geotag to store accurate location.
- Criticality Prediction by ML Model: The machine learning model is used to classify the registered complaints into two categories, critical or not critical.

- Worker Assignment by Administrators: A map interface is provided to administrators to view all complaints in their locality. According to the criticality and urgency of the complaints, admins manually assign complaints to workers.
- Resolving the Issue: Google Maps is used to provide navigation support to workers for better reachability to the complaint sites. Upon completing the work, each worker uploads an image of the complaint site and provides feedback.
- Verification of Completed Work by Administrators: Images and feedback uploaded by workers are verified by administrators ensuring transparency and accuracy. The complaint is marked as completed only after successful verification.

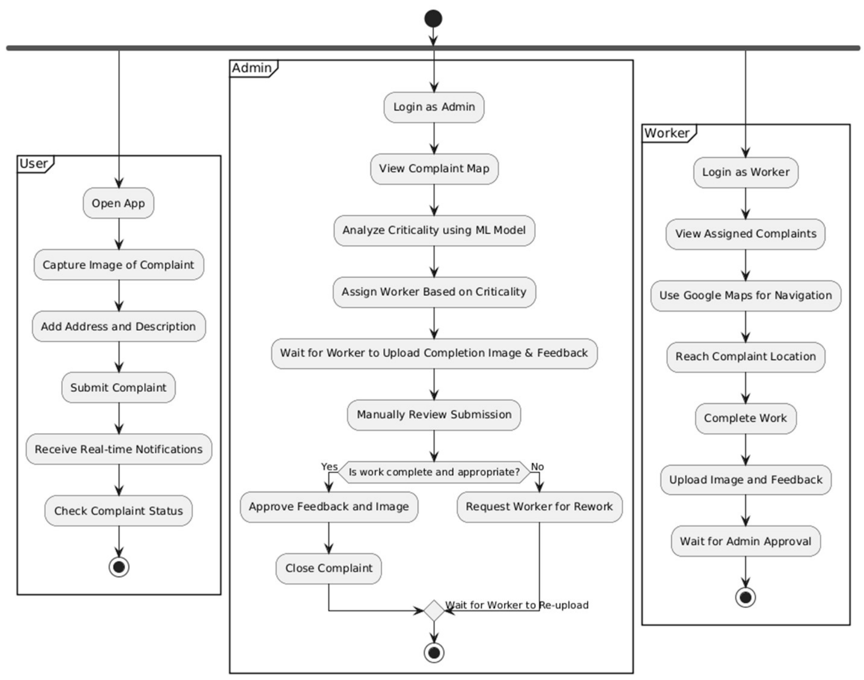

Fig. 2. Workflow of the application.

4. RESULTS

4.1 Citizen Interface and Complaint Submission

The user interface includes a home screen which shows all the complaint categories (Figure 3). From the bottom they can navigate to other parts of the interface including checking their complaint status, notifications and changing account details. Upon selection of the complaint category, users can register their complaint by uploading an image of the complaint site, a short description of the issue and address of the site (Figure 4). Their latitude and longitude are fetched automatically after they grant access to their device's GPS.

Once the complaint is submitted, users receive real-time status updates (Figure 5). The notification system provides real-time complaint tracking which improves user engagement and transparency, keeping citizens informed throughout the complaint lifecycle. The complaint status at different stages of resolution is displayed in the complaint status interface (Figure 6). The initial status of the complaint is “Pending” until the admin reviews it and assesses the criticality predicted by the ML model.

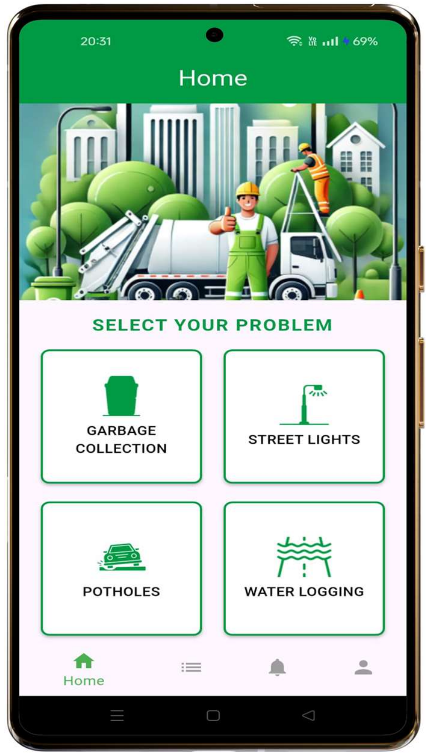

Fig. 3. Home screen for citizens.

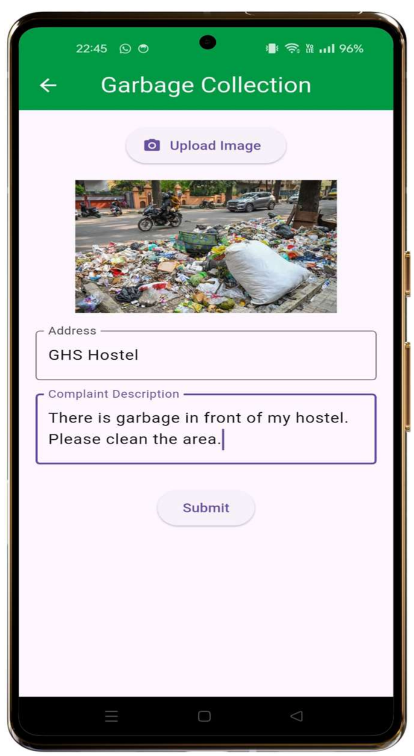

Fig. 4. Complaint entry for citizens.

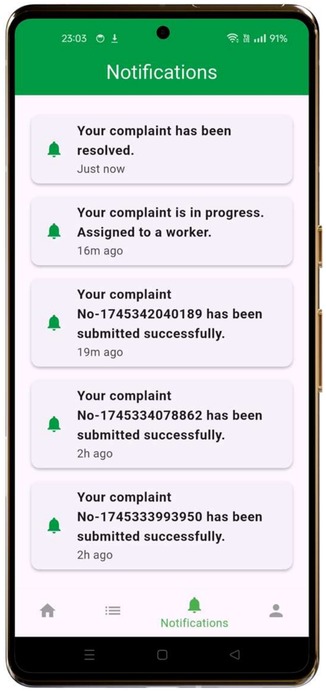

Fig. 5. Real-time updates.

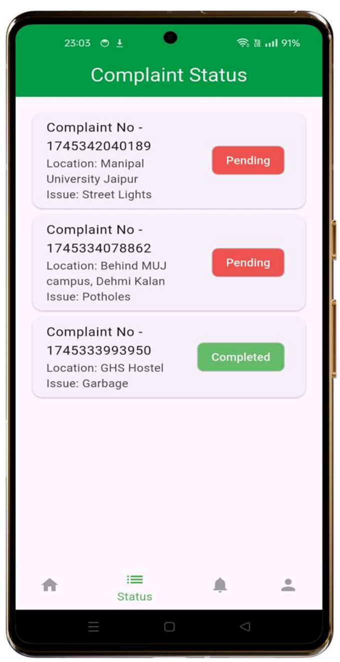

Fig. 6. Complaint status.

4.2 Admin Interface and ML-Based Complaint Classification

On the administrator side, all the registered complaints are visualized on a map interface (Figure 7). Each complaint marker can be tapped to reveal complaint details and manage them (Figure 8). After receiving a new complaint, the image is sent to a trained classification model which predicts whether the complaint is critical or non-critical (Figure 9). It assists the admin in prioritizing complaints.

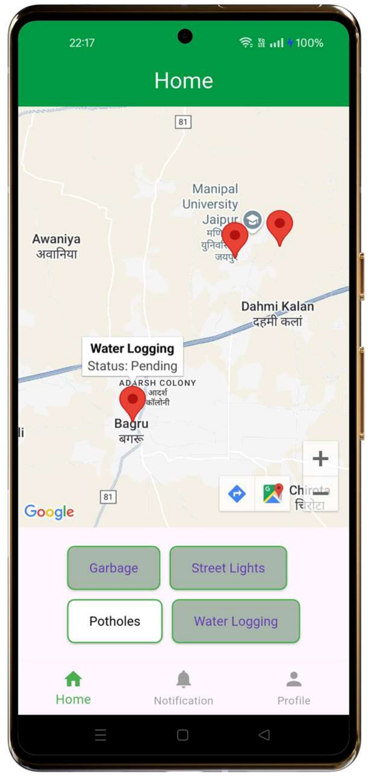

Fig. 7. Home screen for administrators.

Fig. 8. Complaint viewing via markers.

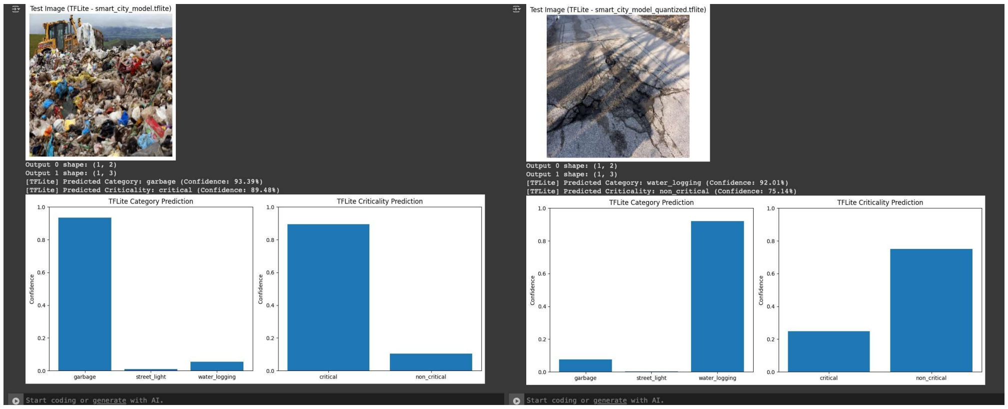

Fig. 9. ML-Based classification interface and complaint prioritization.

Admins then assign complaints to workers based on urgency and criticality (Figure 10 and Figure 11). After assigning complaints to workers, a notification is sent to them, and the status of the complaint is changed to "In Progress" which is also informed to the citizens.

Fig. 10. Manual assignment of workers.

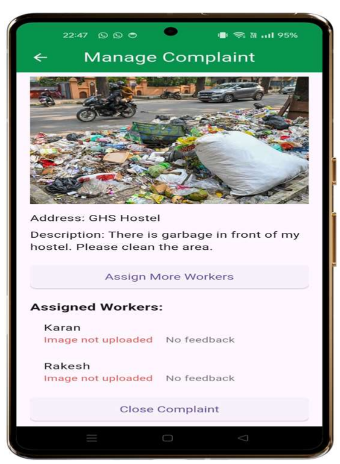

Fig. 11. Displaying assigned workers.

4.3 Worker Module and Field Operations

The interface provided to workers is like admins but with less functionalities. Workers log in to view all the complaints assigned to them on a map interface (Figure 12). They can view complaint details and criticality as well, so they know which tasks to complete first. Navigation support is provided to them via Google Maps to reach complaint sites without any hassle (Figure 13).

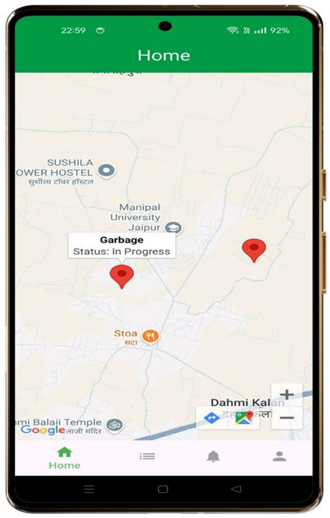

Fig. 12. Home screen for field workers.

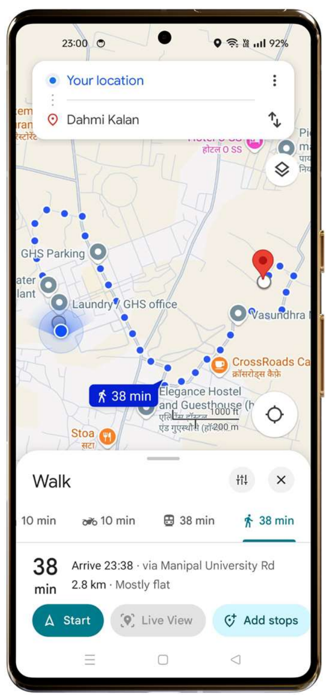

Fig. 13. Navigation support via googles maps.

Upon successful completion of the task, workers are required to upload an image of the complaint site as evidence and provide feedback as well (Figure 14 and Figure 15). In case of any issue faced or false complaints they can report it via feedback to the administrators. The uploaded images and feedback are viewed by admins (Figure 16) and after cross verification the complaints are closed (Figure 17). Complaint status is then changed to “Completed” and citizens as well as workers are notified.

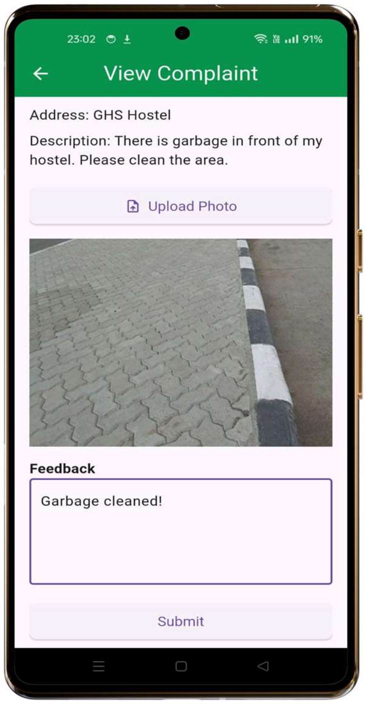

Fig. 14. Uploading image and feedback.

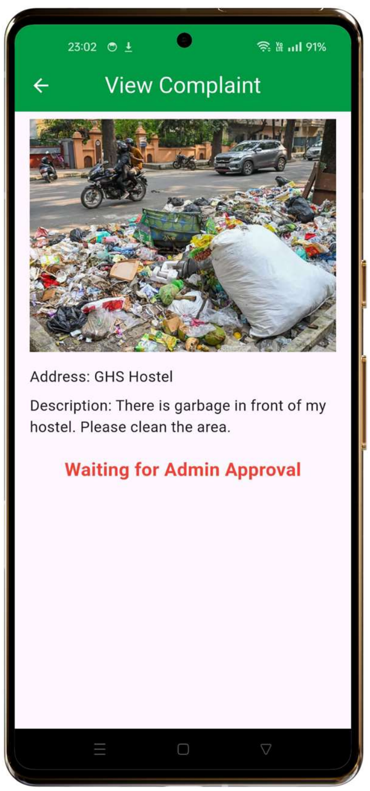

Fig. 15. Waiting for admin approval after submission.

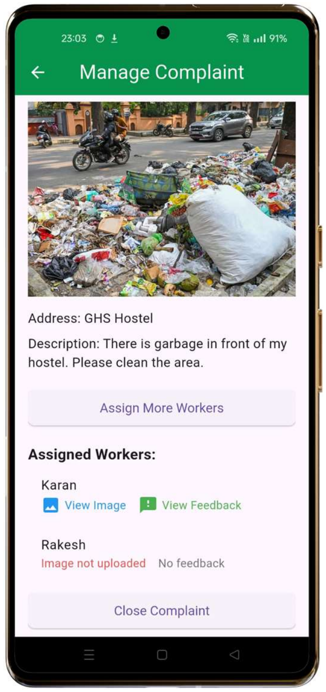

Fig. 16. Manual verification of submitted work.

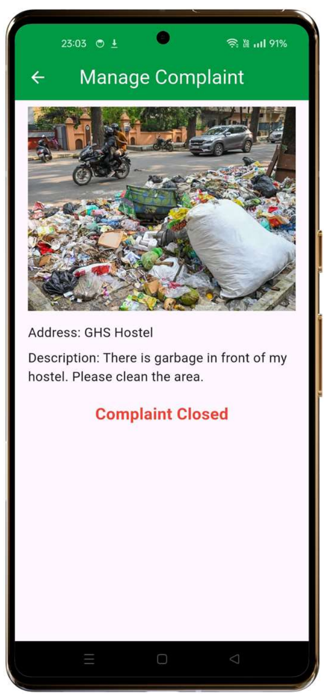

Fig. 17. Closing complaint after successful verification.

5. DISCUSSION

The application provides a reliable and comprehensive solution to urban complaint management. It bridges the gap between all three user roles – citizens, administrators, and field workers. It fosters transparency, accountability, and effective service is delivered with the help of role-specific functionalities provided in the mobile application. The core value of the system is its integration of three distinct user interfaces, each of them tailored to the specific tasks and responsibilities of its users. The three-tier architecture enhances operational flow by preventing any confusion or role overlaps which has been a commonly observed problem in earlier systems. Citizens can easily report issues and get real-time updates, workers can access only the complaints assigned to them while getting navigation support and administrators get to review the criticality predicted by the ML model and manually verify the work done to resolve the complaints. The application uses image-based classification, which is done using the machine learning model. It is better than the conventional text-based systems, as visual classification provides better contextual understanding and aligns better with civic issues where images play an important role. For example, the severity of potholes or the amount of garbage accumulated can be classified easily using images rather than text. The system has a fixed set of complaint categories which makes it less scalable. In the future, adding more complaint categories can make it adaptive to varied civic issues. Another key feature is the map-based complaint visualization which is provided to administrators. It simplifies high-level monitoring and helps in sorting complaints based on categories while identifying complaint-prone areas. Existing systems use maps mainly for user engagement, our application uses geolocator as the main tool for decision-making during resource allocation and worker assignment.

Deliberate design choice for the system was to include manual verification of images uploaded by workers as evidence of their task completion, rather than depending entirely on machine learning. It shows practical understanding of deployment realities. Automation by machine learning model in predicting criticality reduces workload but human interference prevents any kind of misclassification which helps maintain service quality. This hybrid model was developed using knowledge from prior research, where over-automation led to fragile workflows. Our application is also able to scale across urban areas of different sized and administrative complexities. In future, multilingual support can be added and providing offline-first capabilities could increase the user count, mainly in regions with low connectivity or language diversity.

6. CONCLUSIONS

This paper presents a smart city utility management system that follows a three-tier architecture to resolve civic issues efficiently. It enables citizens to register complaints from the mentioned civic issue categories, track updates, and provides a machine learning model which assesses the complaint images and categorizes them as critical or non-critical. This automated categorization helps administrators to prioritize complaints easily and results in fast complaint resolution. It ensures transparency by proof-based complaint resolution. Integrating machine learning, cloud services, and mobile technology enhances responsiveness to civic issues belonging to categories like garbage, potholes, streetlights, and waterlogging. It promotes citizen engagement due to its transparency, security, and real-time complaint tracking support. In future, the system can be extended to include more features like more complaint categories, predictive analysis, and insights into a huge amount of complaint data for administrators. Environmental sensors can also be incorporated to improve accuracy and resource planning.

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Authors Contributions

Khushi Madan assisted in writing the entire mobile app (frontend, backend, and database integration) and wrote the latter half of the manuscript, i.e., the Methods, Results, and Discussion sections. **Avneet Singh Oberoi** collaborated on the development of the mobile application (frontend, backend, and integration of database), wrote the first half of the manuscript such as the Abstract, Introduction, and Related Work, and formatted and organized the references. **Jatinpreet Singh** created the dataset for machine learning, conceptualized and trained the ML model, tested its performance, made all the ML figures and analysis, and helped write and edit the ML sections of the manuscript. All the authors collectively read, edited, and approved the paper's final version.

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