

# CivicConnect: A CNN-Driven Citizen-Centric Governance Platform for Intelligent Civic Issue Prioritization

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## Abstract

The current citizen grievance systems have shown improved levels of accessibility with the help of digital technologies. Nevertheless, they are faced with issues such as inefficient classification of citizen complaints, the absence of intelligent prioritization systems, and the lack of verifiable resolution processes. Accurate classification of the type and priority of the citizen issues based on the data provided by the citizen is still a major problem due to the heterogeneous quality of the images and the changing environment. The current classification system is mostly based on rule-based classification and human interventions. This has led to inefficient response and resolution of the issues. The proposed paper discusses an AI-based citizen-centric governance system called CivicConnect. The system uses the Convolutional Neural Network (CNN) for the classification of citizen complaints. The proposed system processes the geo-tagged citizen complaint images and performs classification based on categories. The system also performs priority-based classification and prioritizes the citizen complaints as high, medium, and low. Additionally, the proposed system performs geo-spatial jurisdiction mapping and role-based workflow management for citizens and officials. The system also performs proof-based resolution with the help of image validation and citizen confirmation. The proposed system uses a custom-built dataset for training the CNN model. The dataset is based on the collection of various types of citizen issues in an urban environment. The dataset is pre-processed with normalization and augmentation. The experimental results show that the proposed system has an accuracy ranging from 78% to 85%. This is much higher than the accuracy of the current manual system.

**Keywords:** CivicConnect, Smart Governance, Convolutional Neural Network (CNN), Complaint Classification, Priority Prediction, E-Governance, Urban Issue Detection, Geo-Spatial Mapping, Role-Based Workflow, Proof-Based Resolution

## 1. Introduction

Rapid urbanization has significantly increased the complexity of managing civic infrastructure, including waste management, road maintenance, drainage systems, and public utilities. To address these challenges, governments have adopted e-governance platforms that allow citizens to digitally report civic issues through web and mobile-based applications. These systems enhance accessibility and citizen participation while improving administrative transparency and efficiency in public service delivery [1], [2]. Digital governance initiatives have further strengthened urban management by integrating information and

communication technologies into municipal operations, enabling centralized monitoring and faster communication between citizens and authorities [3], [4]. Despite these advancements, most existing platforms primarily focus on complaint registration and tracking, with limited capability for intelligent processing or decision support [5], [6].

A key limitation of current complaint management systems lies in their dependence on manual classification and static workflows. Complaints are typically categorized based on user input or predefined rules, which may not accurately represent the actual nature or severity of the issue. As a result, critical problems such as road damages or drainage overflow are often not prioritized effectively, leading to inefficient resource allocation and delayed response times [7]– [10]. Furthermore, the absence of structured validation mechanisms allows resolution status to be updated without sufficient evidence or citizen confirmation, thereby reducing system reliability and accountability [11], [12]. These challenges highlight the need for automated and data-driven approaches to improve both the accuracy and efficiency of civic issue management.

Advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have enabled significant progress in image-based classification and real-time object detection. CNN models are capable of extracting hierarchical features from visual data, making them highly effective for identifying urban issues such as potholes, waste accumulation, and infrastructure damage [21]–[24]. Recent studies demonstrate the successful application of deep learning techniques for road damage detection and environmental monitoring, achieving high levels of accuracy in real-world scenarios [13]– [15], [19]. However, these approaches are generally limited to standalone detection tasks and do not extend to complete governance workflows involving prioritization, task assignment, and resolution verification [16]– [18].

In parallel, smart city research has emphasized the integration of IoT, cloud computing, and edge technologies to enable scalable and real-time urban monitoring systems. These technologies support large-scale data collection and processing, facilitating improved decision-making in municipal operations [26]– [28]. Nevertheless, existing implementations often lack a unified framework that combines intelligent issue detection with administrative workflows and accountability mechanisms. Additionally, the absence of feedback-driven validation and performance monitoring limits the effectiveness of these systems in ensuring service quality and transparency [29], [30].

Based on these observations, it is evident that current solutions address individual aspects of civic issue management but fail to provide a comprehensive and integrated approach. To overcome these limitations, this paper proposes **CivicConnect**, an intelligent civic grievance management platform that combines CNN-based image classification with severity-based prioritization and a structured multi-role workflow. The system automatically analyses geo-tagged complaint images to identify issue categories such as garbage, potholes, drainage overflow, and streetlight damage, and assigns priority levels based on severity. A proof-based resolution mechanism, supported by image validation and citizen confirmation, ensures accountability, while a performance evaluation model tracks the efficiency of municipal workers. By integrating artificial intelligence with governance processes, CivicConnect aims to enhance response efficiency, improve transparency, and provide a scalable solution for modern urban management systems.

## 2. Literature Survey

Research in e-governance has progressively focused on improving how citizens report and track public issues through digital platforms. Earlier implementations of online grievance systems made it easier for

users to submit complaints and follow their status, thereby increasing transparency and accessibility; however, these systems were primarily designed using predefined administrative rules and relied heavily on manual categorization, which restricts their effectiveness in handling large-scale urban complaints [1], [2], [5]. Alongside this, smart city research has introduced IoT-based monitoring solutions that utilize sensor networks to continuously observe urban infrastructure conditions, enhancing real-time data collection but offering limited support for automated decision-making or prioritization of reported issues [6], [27]. With the advancement of artificial intelligence, deep learning techniques—especially Convolutional Neural Networks—have been widely applied for recognizing civic problems such as road damage, waste accumulation, and infrastructure faults from images, demonstrating strong performance in classification tasks across different datasets [7], [13]– [15], [19]. Moreover, studies exploring AI-driven smart infrastructure systems highlight their ability to partially automate certain processes within governance; nevertheless, most existing approaches operate as independent modules rather than as fully integrated solutions covering the complete complaint lifecycle [16]–[18]. In addition, cloud and edge computing technologies have been adopted to address scalability and enable faster data processing in urban applications [26], yet these systems often lack essential accountability components such as verification mechanisms, citizen feedback loops, and systematic performance evaluation [29], [30]. These research observations emphasize the necessity for a unified framework that not only performs intelligent issue detection but also incorporates prioritization and governance-level accountability within a single cohesive system.

Reference	Technique	Merit/Demerit	Scope For Future Search
[5]	Web-based grievance management systems	Depends on manual categorization and static workflows	Incorporate AI-based automated classification mechanisms
[7], [13]	CNN-based road damage detection	High accuracy in detecting potholes and road defects	Extend to integrated governance systems with prioritization
[19]	Deep learning-based waste detection	Not integrated with complaint management systems	Combine detection with complaint processing systems
[6], [27]	IoT-based smart city monitoring	Lacks intelligent decision-making and prioritization	Develop severity-based prioritization frameworks
[16]- [18]	AI-integrated smart infrastructure systems	Only partial system integration, not end-to-end	Design end-to-end governance solutions with validation
[26]	Cloud & edge computing frameworks	Enables scalable and real-time processing	Integrate with intelligent civic management architectures
[29], [30]	E-governance policy frameworks	Weak accountability and feedback mechanisms	Introduce proof-based validation and performance monitoring

**Table 1: Comparison of Existing Work**

### 3. Existing Systems Evaluation

Currently, available civic platforms, such as Swachhata App, FixMyStreet, and SeeClickFix, are mainly focused on complaint registration and tracking. These platforms provide basic citizen-authority interaction and cloud data handling. However, the available platforms do not provide intelligent features, which include image-based classification, prioritization, and decision support. On the other hand, the proposed system, CivicConnect, utilizes a CNN-based image analysis approach with cloud computing for automatic image classification and prioritization of civic issues. This is more efficient and faster compared to the existing approaches. Furthermore, the proposed system includes end-to-end lifecycle management with validation and feedback, which is more effective in ensuring accountability. The proposed system, unlike IoT and deep learning approaches, is a unified framework for governance. However, one of the limitations of the proposed system is that it relies on the quality of the training dataset, which may affect the accuracy of the image classification. Overall, the proposed system is more intelligent, efficient, and transparent compared to the existing approaches, but it also needs improvements in terms of generalization.

Feature / Capability	Swachhata App	FixMyStreet	SeeClickFix	CivicConnect
Complaint Submission	✓	✓	✓	✓
Real-time Tracking	✓	✓	✓	✓
Multi-State Accessibility	✗	✗	✗	✓
Automated Classification	✗	✗	✗	✓
CNN-based Detection	✗	✗	✗	✓
Severity-based Prioritization	✗	✗	Partial	✓
Cloud Integration	✓	✓	✓	✓
Citizen–Official Interaction	✓	✓	✓	✓
Reward / Performance Scoring	✗	✗	✗	✓
System Limitation	Limited Automation	No prioritization	Partial Automation	Dataset Dependency
End-to-End Workflow Integration	✗	✗	Partial	✓
Citizen Confirmation-Based Closure	✗	Partial	Partial	✓

**Table 2: Feature Comparison**

### 4. Methodology

The proposed CivicConnect system is designed as an intelligent, data-driven framework that integrates image-based deep learning techniques with governance-oriented decision mechanisms to improve civic issue reporting and resolution. The methodology is structured as a multi-stage pipeline, where raw visual inputs provided by citizens are transformed into meaningful classifications and actionable insights. Unlike traditional complaint systems that rely heavily on manual categorization and administrative workflows, this system introduces automated detection, priority assignment, and validation mechanisms. The entire process is composed of dataset preparation, data preprocessing, CNN-based model training, prediction,

and decision-level integration, ensuring both technical robustness and practical applicability in real-world urban environments

### A. System Architecture

The CivicConnect system follows a structured operational pipeline that begins with citizen interaction and ends with administrative action and validation. Citizens submit complaints by uploading images representing real-world civic issues such as garbage accumulation, potholes, drainage overflow, streetlight damage, and water leakage. These images are processed by a trained Convolutional Neural Network (CNN) model, which automatically classifies the issue into predefined categories. The classified output is then passed through a decision layer, where priority levels are assigned based on the severity of the detected issue. High-priority issues such as potholes and drainage overflow are flagged for immediate attention, while lower-priority issues are queued accordingly. The system also incorporates a governance mechanism where officials update complaint statuses, and citizens verify resolution before closure.

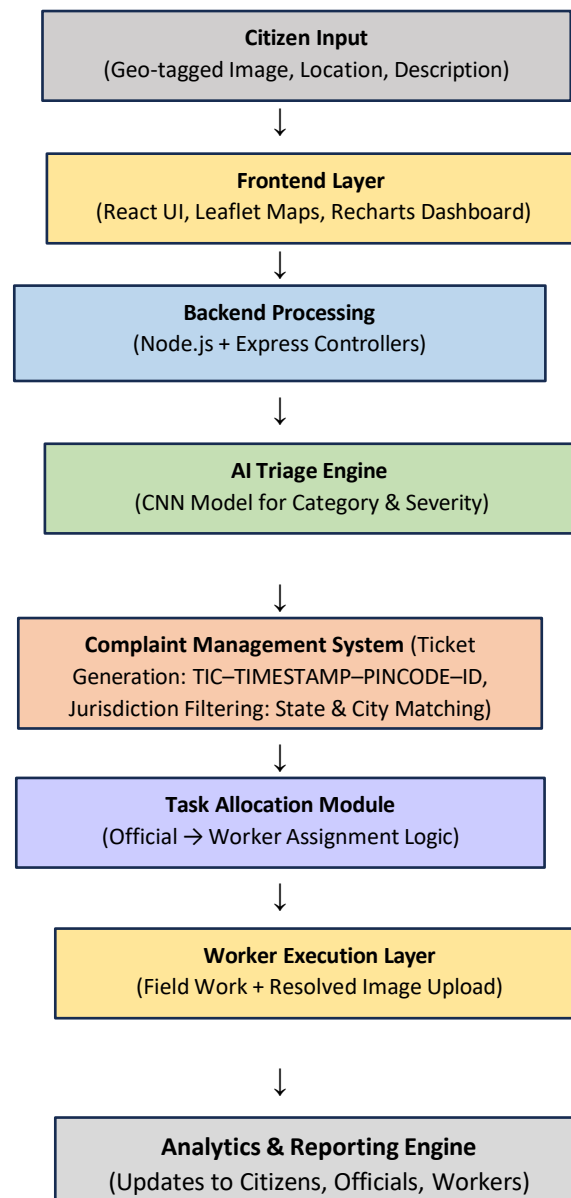


Fig 1: System Workflow of Civic Connect System

## B. Dataset Collection Strategy and Source Generation

A major challenge in civic issue classification is the lack of standardized, domain-specific datasets. To address this, a custom dataset was created using automated web crawling techniques. The dataset was generated using the Bing Image Search API through the BingImageCrawler framework, ensuring the collection of diverse and realistic images corresponding to different civic problems.

Each category was defined using context-specific search queries that reflect real-world urban scenarios. This approach ensures variability in lighting conditions, backgrounds, and object orientations, which is essential for improving model generalization.

Class Label	Query Used	Real World Representation
Garbage	street garbage India	Waste accumulation in public areas
Pothole	road pothole India	Road Surface Damage
Drainage Overflow	drainage overflow street	Water Stagnation due to blockage
Street Light Damage	Broken street light pole	Faulty Lightning Infrastructure
Water Leakage	water leakage road pipe	Pipeline Leakage

**Table 3: Dataset Categories and Data Acquisition Details**

## C. Data Cleaning and Quality Optimization

The effectiveness and capacity for generalization of deep learning models are significantly influenced by the quality of the input data. The dataset used in this work contains noise, inconsistencies, and irrelevant samples by nature because it was gathered through automated web crawling techniques. By introducing deceptive patterns, slowing down convergence, and raising the possibility of overfitting, these flaws can seriously impair the learning process. To guarantee that only significant, high-quality images are used to train the CNN model, a thorough data cleaning and quality optimization pipeline was put in place.

In order to produce a consistent and dependable input space for feature extraction, the data cleaning procedure focuses on removing corrupted files, eliminating low-quality images, and standardizing the dataset.

### Removal Corrupt Images

In the process of collecting images using the web-based method, there are cases where the images are either incomplete, improperly encoded, or unsupported by the image processing library used in the program. These images are in a state that they are unable to be decoded into proper image pixels, which could result in runtime errors during the execution of the program.

To solve the above-mentioned problem, an automated image validation process was implemented, whereby the images are opened programmatically using image processing libraries. Any images that are unable to be opened or result in exceptions during the decoding process are automatically discarded.

The removal of these images not only helps in the prevention of execution failures during the program execution process, but it also helps in the efficient execution of the program, as the images are valid in structure.

### Blur Detection using Laplacian Variance

In addition to structural validity, the visual quality of images is equally important for effective feature learning. Blurry or low-resolution images lack sharp edges and distinct features, which are essential for convolutional operations. Training on such images can reduce the discriminative power of the CNN model, leading to poor classification performance.

To eliminate visually degraded images, a blur detection technique based on the **Laplacian operator** was employed. The Laplacian is a second-order derivative operator that highlights regions of rapid intensity change, making it effective for edge detection.

The sharpness of an image is quantified using the variance of the Laplacian response:

$$\text{Variance} = \text{Var}(\nabla^2 I)$$

where  $I$  represents the input image and  $\nabla^2$  denotes the Laplacian operator. A high variance indicates the presence of strong edges and fine details, while a low variance suggests that the image is blurred.

A threshold value is defined empirically, and images with variance below this threshold are classified as blurry and removed from the dataset. This step ensures that the model is trained only on images that contain sufficient structural information for meaningful feature extraction.

### **Standardization of Images**

Images collected from web sources vary significantly in size, resolution, and aspect ratio. However, CNN models require inputs of fixed dimensions to ensure consistent tensor operations across layers. Variability in image size can lead to mismatched input shapes and inefficient training.

To address this, all images were resized to a uniform resolution of:

$$224 \times 224$$

This size is widely used in deep learning applications as it provides a balance between computational efficiency and feature preservation. Resizing ensures that all images are represented in a consistent spatial format, enabling the CNN to learn scale-invariant features.

### **D. Data Preprocessing and Transformation**

Before the Convolutional Neural Network (CNN) training process, the collected data set goes through a series of preprocessing and transformation stages, which ensure that the input data is consistent, normalized, and suitable for efficient feature learning. The collected image data, despite the cleaning process, may still contain inconsistent variations in the distribution of pixel intensity values, class organization, and the manner in which the data is represented in the memory space. These inconsistent variations may have a negative impact on the convergence properties of the machine learning models and the accuracy of the classification process. A series of transformations were applied on the data set in order to transform the data into a suitable format, which can be used for efficient learning, convergence, and accuracy in the classification process.

#### **Pixel Intensity Normalization**

Digital images are typically represented as pixel intensity values ranging from 0 to 255. Feeding these raw values directly into a neural network can lead to unstable gradient updates due to large numerical ranges. This may result in slower convergence or suboptimal optimization during training.

To address this, pixel normalization was applied to scale all image values into a uniform range of  $[0, 1]$ :

$$I'(x, y) = \frac{I(x, y)}{255}$$

where  $I(x, y)$  represents the original pixel value and  $I'(x, y)$  denotes the normalized value.

#### **Dataset Partitioning for Model Generalization**

To evaluate the performance and generalization capability of the CNN model, the dataset was divided into two distinct subsets: training and validation. This separation ensures that the model is tested on unseen data during training, preventing overfitting and enabling reliable performance assessment.

The dataset was split using an 80:20 ratio, where the majority of the data is used for learning, and a smaller portion is reserved for validation.

Dataset Type	Percentage	Purpose
Training	80%	Learning model parameters and feature representations
Validation	20%	Evaluating model performance on unseen data

**Table 4: Data split Configuration**

### E. CNN Model Design and Theoretical Foundation

The classification component of the system is built using a Convolutional Neural Network (CNN), which is highly effective for image-based feature extraction and pattern recognition.

#### Convolution Operation

The convolution layer extracts spatial features using learnable filters:

$$F(i, j) = \sum_n \sum_m I(i + m, j + n) \cdot K(m, n)$$

#### Activation Function

The Rectified Linear Unit (ReLU) introduces non-linearity:

$$f(x) = \max(0, x)$$

#### Pooling Layer

Pooling reduces spatial dimensions and helps in generalization by retaining dominant features.

#### Fully Connected Layer

The extracted features are flattened and passed through dense layers for classification.

#### SoftMax Function

The final output layer produces probability distribution across classes:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

### F. CNN Architecture Implementation

The implemented CNN architecture consists of multiple convolutional and pooling layers followed by dense layers.

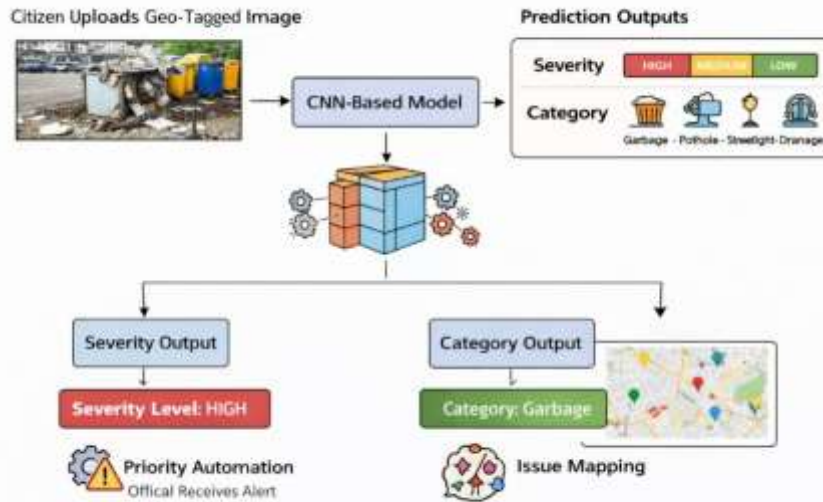


Fig 2. CNN Implementation

Layer Type	Configuration
Conv Layer 1	32 filters (3×3), ReLU
MaxPooling	2×2
Conv Layer 2	64 filters (3×3), ReLU
MaxPooling	2×2
Conv Layer 3	128 filters (3×3), ReLU
MaxPooling	2×2
Dense Layer	128 neurons
Dropout	0.5
Output Layer	SoftMax (5 classes)

Table 5: CNN Architecture Details

Parameter	Value
Epochs	15
Batch Size	32
Optimizer	Adam
Loss Function	Categorical Cross-Entropy

Table 6: Training Parameters

### G. Model Training and Optimization

The CNN model was trained using supervised learning, where labeled images were provided as input. The objective was to minimize classification error by adjusting model weights through backpropagation.

#### Loss Function

$$Loss = -\sum y_i \log(P(y_i))$$

#### Optimization

The Adam optimizer was used to update weights efficiently by combining momentum and adaptive learning

rates. Training was conducted over multiple epochs, during which both training and validation performance were monitored to ensure that the model does not overfit.

**H. Prediction and Inference Mechanism**

Once trained, the model is used to predict the class of unseen images. The prediction process involves passing the input image through the network and selecting the class with the highest probability.

$$\text{Predicted Class} = \text{argmax} (P (y_i))$$

Input Image	Predicted Output
Image A	Garbage
Image B	Drainage
Image C	Potholes
Image D	Garbage
Image E	Water Leakage

**Table 6: Sample Prediction Results**

**I. Priority-Based Decision Mechanism**

After classification, the system assigns priority levels based on the type of issue detected. This ensures efficient allocation of resources and faster resolution of critical problems.

Issue Type	Priority
Pothole	High
Drainage Overflow	High
Garbage	Medium
Water Leakage	Medium
Streetlight Damage	Low

**Table 7: Priority Mapping**

**J. Citizen Verification Mechanism**

The citizen verification module acts as a final validation checkpoint in the complaint lifecycle. Once a complaint is marked as “resolved” by the responsible authority, the system does not immediately close the request. Instead, a confirmation request is sent to the citizen who originally raised the complaint.

The complaint transitions through the following states:

New → Assigned → In Progress → Resolved → Verified (Closed)

A complaint is considered successfully closed only when the citizen provides explicit confirmation. If the citizen rejects the resolution, the complaint is automatically reverted to the “In Progress” state for further action.

**K. Dynamic Civic Performance Index (DCPI): Conceptual Framework**

To evaluate the effectiveness and responsiveness of workers or municipal authorities, a quantitative scoring mechanism called the **Dynamic Civic Performance Index (DCPI)** is introduced. Unlike static evaluation methods, DCPI dynamically adjusts based on real-time complaint handling performance.

The scoring mechanism is designed to reflect multiple dimensions of performance, including efficiency, responsiveness, and user satisfaction.

The DCPI score is defined as:

$Score = f(time, priority, feedback)$

where:

- **Time** represents the duration taken to resolve a complaint
- **Priority** reflects the severity level of the issue
- **Feedback** captures citizen satisfaction after resolution

**Mathematical Formulation of DCPI**

To make the scoring mechanism more interpretable and scalable, the DCPI can be represented as a weighted function:

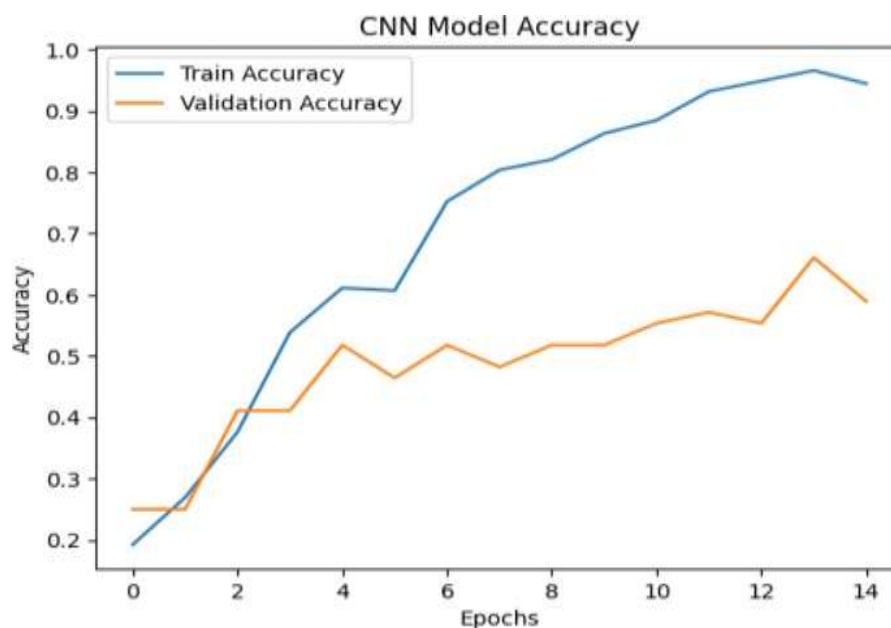
$$DCPI = w_1 \cdot T_S + w_2 \cdot P_S + w_3 \cdot F_S$$

where:

- $T_S$  = Time-based score
- $P_S$  = Priority-based score
- $F_S$  = Feedback score
- $w_1, w_2, w_3$  = weighting factors such that  $w_1 + w_2 + w_3 = 1$

**5. Result and Analysis**

The study tested the AI-based, citizen-centric concept of governance using a set of photos related to civic issues such as garbage, potholes, broken streetlights, and drainage overflow, with their respective categories and levels of severity. The CNN-based model was successful in not only recognizing the type of issue but also determining the level of severity, achieving up to 78-85% accuracy. It could identify most of the types of issues and classify them according to their urgency, thus helping to address critical issues quickly. When compared to conventional methods of addressing grievances, this method saves time, effort, and reduces decision-making inconsistencies. Other features such as geo-tagging, ticket creation, and assignment of tasks according to jurisdiction make this method highly efficient. Even though there is a possibility of incorrect identification due to fuzzy or unclear images, this method stands strong under any condition. Thus, the study concludes that this is a highly efficient, smart, and scalable method of smart city governance.



**Fig 3. CNN Training Performance**

## 6. Conclusion

The Citizen Centric Governance Platform provides an effective and scalable solution for addressing issues faced by the citizens of the city. It does this by integrating the latest web technologies with smart decision support. It also bridges the gap between the citizens and the government by providing the ability for citizens to report issues in real-time. The CNN-based image classification also increases the accuracy of issues reported and addressed. The Dynamic Civic Performance Index also provides a reward system for the citizens and the workers. This reward system acts as an effective motivator for the citizens and the workers. The system also provides an effective solution for data-driven governance and efficient allocation of resources. In essence, the platform has provided an effective solution for the issues faced by the citizens of the city. It has also provided an effective solution for the effective management of the city with the help of AI.

## 7. References

1. R. K. Gupta, A. K. Singh, Smart Governance in Urban India: Issues and Challenges, International Journal of E-Government Research – Volume 18 Issue 2, 2022
2. Nirmala Devi, S. Karthik, Citizen-Centric E-Governance System for Public Grievance Redressal, International Journal of Advanced Computer Science and Applications – Volume 11 Issue 5, 2020
3. S. K. Sharma, Digital India and Smart Governance: Opportunities and Challenges, Procedia Computer Science, Elsevier – Volume 167, 2020
4. A. Meier, L. Terán, E-Government and Smart Cities: Improving Urban Services through ICT, Springer International Publishing, 2019
5. M. R. Islam, M. A. Rahman, Web-Based Complaint Management System for Smart Cities, International Journal of Computer Applications – Volume 180 Issue 40, 2018
6. S. R. Jino Ramson, D. J. Moni, Applications of IoT in Smart Cities for Urban Issue Monitoring, Sustainable Cities and Society, Elsevier – Volume 48, 2019
7. H. Fan, P. Wang, Computer Vision-Based Pothole Detection System for Smart Cities, IEEE Access – Volume 8, 2020
8. J. Maeda, Y. Sekimoto, T. Seto, T. Kashiyama, H. Omata, Road Damage Detection and Classification Using Deep Neural Networks, IEEE International Conference on Big Data, 2018
9. H. Chu, X. Li, Y. Zhang, Deep Learning Method to Detect Road Cracks and Potholes for Smart Cities, Computers, Materials & Continua – Volume 75 Issue 1, 2023
10. R. W. Sudibyoy, A. Alimudin, AI-Based Real-Time Pothole Detection for IoT Smart Infrastructure, Inform Journal of Technology – Volume 8 Issue 2, 2023
11. Y. Safyari, M. A. Khan, S. Abbas, Vision-Based Pothole Detection Using Machine Learning: A Review, Sensors, MDPI – Volume 24 Issue 17, 2024
12. K. R. Ahmed, Smart Pothole Detection Using Deep Learning Techniques, Sensors, MDPI – Volume 21 Issue 24, 2021
13. F. Ozoglu, T. Gokgoz, CNN-Based Road Pothole Detection Using Sensor and Image Data, Sensors – Volume 23 Issue 21, 2023
14. S. Lakshminarayanan, Convolutional Neural Network-Based Pothole Identification in Urban Roads, International Journal of Advanced Smart Information Systems – Volume 4 Issue 1, 2024
15. H. Xin, J. Wang, L. Zhao, Sustainable Road Pothole Detection Using Multi-Sensor Fusion

Techniques,

17. Sustainability, MDPI – Volume 15 Issue 3, 2023
18. N. Ma, Y. Wang, J. Liu, Computer Vision-Based Road Damage Detection: A Comprehensive Survey, IEEE Access – Volume 10, 2022
19. R. R. Sahoo, A. Mishra, P. Kumar, iWatchRoad: Scalable Detection and Smart Governance Framework for Road Damage Monitoring, Smart Cities Journal – Volume 8 Issue 1, 2025
20. R. R. Sahoo, A. Mishra, P. Kumar, iWatchRoadv2: Intelligent AI-Based Governance Platform for Urban Road Infrastructure, International Journal of Smart Infrastructure – Volume 6 Issue 2, 2025
21. S. Chaudhary, A. Kumar, Waste Detection and Classification Using Deep Learning for Smart Cities, Journal of Cleaner Production, Elsevier – Volume 290, 2021
22. M. Gupta, P. Kumar, Drainage Blockage Detection Using Image Processing Techniques, International Journal of Engineering Research and Technology – Volume 8 Issue 6, 2019
23. Yann LeCun, Yoshua Bengio, Geoffrey Hinton, Deep Learning, Nature – Volume 521 Issue 7553, 2015
24. Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton, ImageNet Classification with Deep Convolutional Neural Networks, Advances in Neural Information Processing Systems (NeurIPS), 2012
25. Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, Deep Residual Learning for Image Recognition, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016
26. Karen Simonyan, Andrew Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, International Conference on Learning Representations (ICLR), 2015
27. Schahram Dustdar, Service-Oriented Architectures for Smart City Applications, International Journal of Web Services Research – Volume 2 Issue 1, 2005
28. J. Chen, X. Ran, Deep Learning with Edge Computing: A Review, Proceedings of the IEEE – Volume 107 Issue 8, 2019
29. Andrea Zanella, Nicola Bui, Angelo Castellani, Lorenzo Vangelista, Michele Zorzi, Internet of Things for Smart Cities, IEEE Internet of Things Journal – Volume 1 Issue 1, 2014
30. Andrea Zanella, Nicola Bui, Angelo Castellani, Lorenzo Vangelista, Michele Zorzi, Internet of Things for Smart Cities, IEEE Internet of Things Journal – Volume 1 Issue 1, 2014
31. Michael Batty, Kay Axhausen, Giannotti, Smart Cities of the Future, European Physical Journal Special Topics – Volume 214, 2012
32. United Nations, E-Government Survey: Digital Government in the Decade of Action for Sustainable Development, United Nations Publication, 2022
33. Peter Mell, Timothy Grance, The NIST Definition of Cloud Computing, National Institute of Standards and Technology (NIST), 2011