UTILIZING OPENCV FOR REAL-TIME IMAGE PROCESSING URBAN STREET CLEANLINESS ASSESSMENT

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Abstract— **Street cleanliness in urban areas functions as a vital factor that affects public health standards and environmental sustainability together with urban resident well-being. Street cleanliness assessment through manual inspections takes too much time and labour while remaining subject to personal interpretation. CNN operate for waste classification by separating different kinds of pollutants. The performance evaluation of this system depends on its accuracy for detection together with its processing capability and its ability to work in diverse environmental situations. Traditional methods are replaced by this automated system which delivers objective and scalable and cost-effective cleanliness monitoring capabilities. The OpenCV system reduces manual work while achieving equivalent detection precision in its preliminary testing phase. System performance receives improvements through solutions that handle issues with occlusion and lighting variations and the optimization of computational efficiency. The research advances smart city programs through its presentation of a technological structure that enhances urban sanitation management effectiveness. This research establishes automated cleanliness assessment as a data-supported approach for enhancing waste management methods that results in improved urban environmental cleanliness and health.**

Keywords: OpenCV, real-time image processing, urban street cleanliness, computer vision, litter detection, smart city, waste classification, environmental monitoring.

1.INTRODUCTION

The condition of urban streets acts as a fundamental element which impacts both public health norms and environmental sustainability along with resident welfare in urban areas [1]. Manual street inspections for cleanliness assessment require abundant human resources and time yet their results remain open to interpretive variation. A Convolutional Neural Network (CNN) functions as a waste classification system through separation of various types of pollutants [2]. The performance evaluation of this system depends on its detection accuracy as well as its processing speed and its operational capacity across different environmental conditions [3]. The automated system implements objective scalable and cost-effective monitoring capabilities for cleanliness assessment [4]. The OpenCV system eliminates manual work because it reaches the same detection accuracy levels during its initial testing phase [5]. The system achieves performance enhancement through optimized solutions that optimize both occlusion management and lighting condition processing and computational efficiency [6]. The research enables progress in smart city programs by developing technological infrastructure which improves urban sanitation management effectiveness [7]. The research demonstrates automated cleanliness assessment as an evidence-based method to enhance waste management practices which leads to better urban environmental cleanliness and health conditions [8]. Maintaining street cleanliness becomes a challenging task for cities that operate at high levels of activity. Municipalities struggle to inspect every street during their surveillance operations. Traditional street inspections using human observation led to incorrect and slow decision-making processes. We plan to employ the OpenCV tool to inspect street images for their environmental cleanliness levels. The proposed system offers potential to transform urban cleaning operations [9]. OpenCV serves as the main tool for analyzing street imagery through real-time operations in this project. OpenCV functions as a sophisticated computer tool that enables machines to interpret visual information [10]. The combination of OpenCV technology and additional smart tools aims to deliver efficient street cleanliness evaluation.

The primary operation of this project involves acquiring numerous images of urban streets through sensor and camera systems. The images provide visual information about the presence of street debris and street dirt. The system performs analysis through OpenCV rather than depending on human evaluators. OpenCV operates as a real-time assessment tool which detects trash or dirt at high speed [11].

OpenCV improves image clarity while simultaneously detecting waste features in pictures. OpenCV helps decrease the time needed to evaluate cleanliness conditions. Streets must remain clean because they support both public contentment and city wellness [12]. Mobile edge computing helps us function as an additional supporting system. The system functions as a nearby processing server which delivers quick data management [13]. Through this technology our system develops the ability to recognize trash and unclean areas. The computer system gradually develops higher precision in detecting such problems in images [14].

This project demonstrates the possibility to revolutionize how urban sanitation services are managed. OpenCV and other tools enable quick and accurate assessment of street cleanliness. The system enhances urban areas by creating better living conditions that lead to improved resident well-being [15].

A. MOTIVATION:

In environment poor streets are a source of pollution, clogged drainage systems and spread of diseases and are a threat to residents and the ecosystem. Manual inspections are a traditional method of street cleanliness monitoring that is time consuming, labor intensive and subjective. However, the scalability and real time assessment are not available in the conventional approaches, which makes it difficult for municipal authorities to respond in time to cleanliness issues. The reason for using OpenCV for real time image processing in urban street cleanliness assessment is due to the necessity of an efficient, automated and data driven solution.

As automated street cleanliness monitoring is a real time image analysis problem, OpenCV, an open-source computer vision library, offers powerful tools for real time image analysis, and is thus a good choice. OpenCV integrates machine learning, deep learning techniques to perform accurate waste detection, classification and pattern recognition to reduce human errors made in the cleanliness assessment. This study was motivated by the gap between traditional street cleanliness assessment methods and modern AI driven solutions and seeks to provide more efficient and objective system that is beneficial to city administrators and the general public. Since automated street cleanliness monitoring requires real-time image analysis, OpenCV, an open-source computer vision library, is a good choice. OpenCV integrates machine learning and deep learning techniques to accurately detect, classify and recognize waste pattern without human errors in cleanliness assessment. The reason for using OpenCV for real time image processing for urban street cleanliness assessment is that an efficient, automated and data driven solution is required. This study was motivated to fill the gap between existing traditional street cleanliness assessment methods and modern AI based solution, to introduce a more efficient and objective system for both the city administrators and the general public. By enhancing waste management strategies in a smart way, this approach helps smart city initiatives to optimize waste management strategies, decrease operation costs and enhance urban sustainability.

B. OBJECTIVES:

The main goal of this project is to create a strong and efficient system for checking how clean urban streets are in real-time using OpenCV. This system will use OpenCV's wide range of programming functions for real-time computer vision to process images from smart sensors and cameras set up around cities. The key goals include:

Improving Image Processing Abilities:

Use OpenCV's advanced tools to find, classify, and measure street cleanliness signs like litter, debris, and graffiti. Apply methods such as edge detection, contour finding, and object recognition to accurately spot cleanliness issues in different lighting and weather conditions.

Using Mobile Edge Computing:

Set up a mobile edge computing system to process data near where it is collected, reducing delays and allowing real-time analysis. Manage large amounts of image data efficiently to avoid delays caused by centralized data processing.

Adding Deep Learning Methods:

Enhance traditional image processing with deep learning models to better recognize and classify cleanliness indicators. Train convolutional neural networks (CNNs) and other deep learning models on large datasets to increase the system's accuracy and ability to adapt over time.

Real-Time Assessment and Decision Making:

Develop a system that provides instant feedback on street cleanliness, enabling quick maintenance and timely actions. Ensure the system reacts swiftly to real-time data, helping city management keep streets cleaner and healthier.

Scalability and Reliability:

The system must scale across various urban sizes and complexities of different areas. Additionally, it should maintain high reliability to minimize false results in cleanliness measurements for accurate data collection. This research targets the development of an advanced system to enhance urban street cleanliness management through successful achievement of its designed goals.

II. LITERATURE SURVEY

The model is designed to help planners conceptualize the development of innovation ecosystems within smart cities. This work provides a structured approach to integrating various technological, social, and economic components essential for building smart city environments [1] How data services that focus on citizens can enhance the development of smarter cities. The authors discuss the importance of integrating citizen-centric approaches in the management and utilization of urban data to improve city services and infrastructure [2] vision for automatic waste classification in Colombian high schools. This study was included in the proceedings of the Networked Electronic Media conference [3] Chua Kim Hing and Hai Jon gung gut proposed a new model for maintaining urban cleanliness in their 2018 work.[4] analyze and evaluate a smart city architecture that provides service APIs. This research focuses on the knowledge-based framework designed to enhance urban services.[5] at the 13th International Conference on Software Engineering and Knowledge Engineering (SEKE) in San Francisco, CA, USA, in 2018, and is documented on pages 675-681 of the conference proceedings [6] smart city and lifecycle concepts to improve the management of large-scale events. This research was included in the proceedings of the IFIP International Conference on Product Lifecycle Management [7] Characterization of pollutants in Florida street sweepings for management and reuse," which was published in the Journal of Environmental Management. This study delved into the analysis of pollutants present in street sweepings in Florida, aiming to develop strategies for their effective management and potential reuse. Characterization of pollutants in Florida street sweepings for management and reuse," which was published in the Journal of Environmental. Management. This study delved into the analysis of pollutants present in street sweepings in Florida, aiming to develop strategies for their effective management and potential reuse [8].

Smart technology integration with urban settings has enabled new developments in urban management systems particularly related to cleanliness assessment. Smart city ecosystem models serve as fundamental tools for planners who need to create sustainable development frameworks by merging technological, social and economic systems (Alcocer & Cruz, 2019) [9]. The research explores resident-focused data services which improve smart city implementation through personalized services based on actual community needs (Granell et al., 2016) [10]. Research into waste management improvement conducted in Colombia's educational institutions demonstrated automatic waste classification systems which aimed to train students about effective waste practices (Gómez et al., 2017) [11]. Chua and Gung gut (2018) [12] developed a systematic cleanliness model which includes community involvement with policy backing and technological solutions for maintaining urban hygiene. Nguyen et al. (2018) evaluated knowledge-based smart city architecture frameworks for their delivery of real-time services through open APIs that enabled urban service transparency and interoperability (Nguyen et al., 2018) [13]. The SEKE conference investigated system design relevance for city operations through discussions about urban service integration software engineering approaches (SEKE Proceedings, 2018) [14]. Large-scale event management achieves benefits through lifecycle-based smart city frameworks which enable real-time decision systems and waste flow management capabilities (Stark et al., 2017) [15]. A research paper from the Journal of Environmental Management investigated Florida street sweepings to identify pollution contents which revealed environmental effects of urban cleaning practices and potential reuse applications (Shah et al., 2017) [16]. Scientists have expanded the research of waste detection technologies by developing real-time systems with advanced computer vision systems. The system developed by Wang et al. (2020) integrated Faster R-CNN with edge computing to establish a real-time street litter detection platform for urban road waste sorting [17]. The research by Ahmed et al. (2022) demonstrated that Mask R-CNN technology enables real-time road damage assessment which directs municipal maintenance operations [18]. Salih et al. (2023) conducted a mapping review of computer vision applications in smart cities which included traffic control and environmental cleanliness domains [19]. The Plast O Pol dataset served to assess the performance of YOLOv5 and Retina Net object detection models for automated litter detection according to Smets et al. (2022) [20]. The research by Li et al. (2023) presented MGB-YOLO for detecting manhole covers which demonstrates its capacity to prevent accidents from open or improperly placed covers [21]. The video detection system of OpenCV serves as a crucial element in urban surveillance and cleanliness systems which Learn OpenCV (2020) demonstrated through its presentation of contour and background subtraction methods for outdoor applications [22]. The research of Zhou et al. (2021) used deep convolutional neural networks to analyze Google Street View pictures for extracting urban perception and cleanliness data [23].The research by Choudhury et al. (2022) integrated environmental surveillance with behavioral assessment through their work that utilized YOLOv5 alongside facial recognition for detecting littering on streets [24].The research conducted by Basak et al. (2023) examined 65 studies regarding computer vision applications in urban waste management which demonstrated that AI-based litter detection systems decrease municipal waste collection expenses while enhancing urban hygiene performance [25].

A. DATA COLLECTION AND MOBILE EDGE

1) DATA COLLECTION

The principal duty in the data collection phase consists of obtaining both garbage images and street photos required by the assessment system. The vehicle with high-resolution camera gathers street image data and local management information while operating in urban streets. The cleaning vehicle with its high-resolution camera operates on each street route based on administrator assignments to gather street image data. The administrator determines the distance between each shooting point and the cleaning vehicle photographs the area from four directions at each point to create images covering between 150–300 m² of space [1, 2]. Mobile station rules include maintaining fixed image resolution and traveling at 25 kilometers per hour with pictures taken at specific distances that produce four images at each point [3]. The mobile station transmits its position frequently to the city management center for local information purposes which enables administrators to send cleaning staff immediately when required [4] [5].

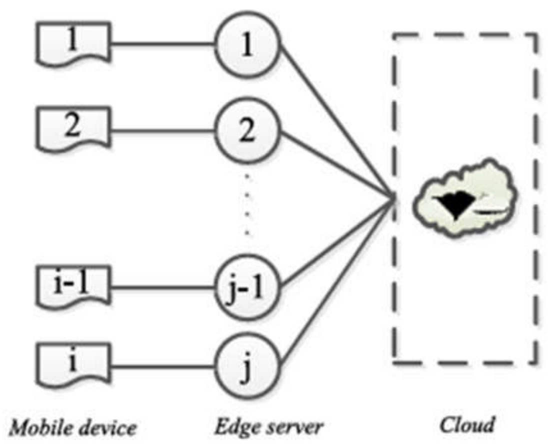

Fig 1. Street image data preprocessing in the edge environment

2) MOBILE EDGE PROCESSING

Two tasks are performed by edge servers. The first thing is to improve the system performance as a whole. At this stage, when object detection is done, the image data collected is fed into the CNN network and then the size of pictures is changed to the proper size. We assume that if the image data is preprocesses in the edge server, the time of the entire system will be reduced. An algorithm is designed to change the image size automatically in the edge server when transmitting image data to the edge server. The street image data preprocessing in a mobile edge environment is shown in Fig. 1. Street image data from mobile device i is sent to edge server j. We define $t\ i-j$ t i–j when the time street image data is transferred from mobile device i to edge

server j. $t\,j - c$ t j−c the time from edge server j to cloud c, … t edge t edge the time that the picture is processed in the edge server [1], [2], [3].
Total time of mobile edge processing is calculated using the following formulae (1):

$$T = t_{i-j} + t_{edge} + t_{j-c} \tag{1}$$

B. IMAGE DETECTION USING NEURAL NETWORK

1) NETWORK STRUCTURE

The main responsibility in data collection involves obtaining the necessary images and garbage data for assessment methods. The combination of street image data and local management data represents the main output of vehicles equipped with high-resolution cameras when operating in city streets [1].
The cleaning vehicle with its high-resolution camera follows administrator instructions to capture street images on each street. The cleaning vehicle photographs four directions at each shooting point which the administrator defines the distance between these points. The shooting range spans between 150–300 m² of space [2].
The operational rules for mobile stations include the following: Fixed image resolution; Vehicle speed of approximately 25 kilometers per hour; The points for shooting should be placed at regular distances from one another. Four images captured per point [3]. The mobile station sends local management information about its current position to the city management platform through regular transmissions. The city administrator obtains immediate visibility to deploy cleaning staff for addressing detected street waste or contamination [4].

2) NETWORK TRAINING

This section focuses on selecting and designing the network structure as its main responsibility. The CNN network accepts images of any dimension at its input stage to produce feature maps as its first operation. The ZF-Net architecture serves as the CNN selection for this project according to Zeiler and Fergus [1].

The network begins by processing a 224×224 RGB image (3 channels) through its first layer which contains 96 filters. The filter size in the first layer measures 7×7 to prevent convolution filters from combining high-frequency and low-frequency components and dropping intermediate frequency values [2]. After the operation, max pooling reduces dimensions through its stride of 2 while maintaining vital characteristics.

The first convolutional layer generates 96 feature maps that have a dimension of 55×55 pixels. Each successive layer from 2 to 5 follows a similar pattern of operations leading to 256 feature maps of dimension 6×6 according to [3].

The fully connected layers appear in positions six and seven of the network. The feature output from Layer 5 proceeds to two heads which receive the output. The classifier function establishes the category for the region proposal. The bounding box regressor determines the specific location information of detected objects [4].

3) STREET GARBAGE DETECTION

The trained model operates during this stage to identify street trash. CNN receives street images as input to extract image features that it projects onto a feature map by performing convolutional operations [1]. RPN generates about 300 region proposal boxes per image which serve as potential object areas [2].
The proposal boxes travel through two network layers for classification and regression purposes to identify the object type and adjust the bounding box coordinates [3]. A detection counting system has been established to measure the results. The count function increases by one whenever the region proposal box gets generated and gets identified as containing garbage according to formulae 2.

$$C(f; D) = \sum_{i=1}^{m} \mathbb{I}(f(x_i) = y_i) \tag{2}$$

C. MULTI-LEVEL CLEANLINESS ASSESSMENT MODLE

1) STREET LAYER ASSESSMENT

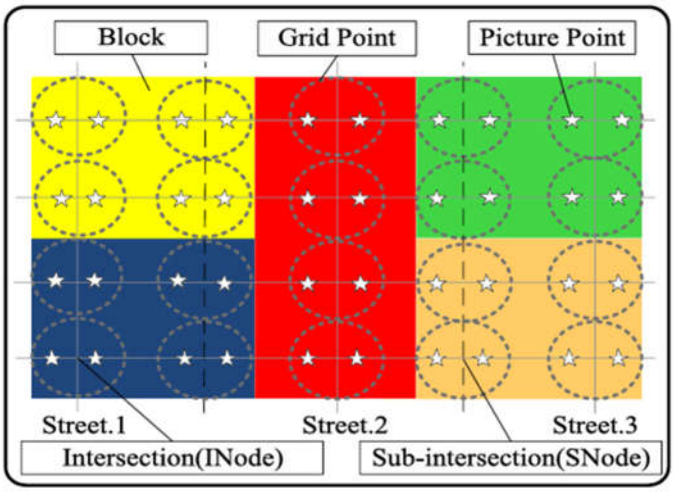

Fig 2. Grid architecture.

The street layer assessment is the basis of the level assessment model and it plays a key role in the entire assessment system. At this layer, each street has several photo points, and at least four photos are taken at each point. The distance between the two photo points is determined by City administrators. Fig. 2 shows a street layer assessment. Each photo point is shot in Front, Back, Left, and Right directions. If there is garbage in the photos, street layer cleanliness can be assessed through these pictures. As we can see from Fig. 6, a street passes through multiple grid points. The assessment value of each street is the average value of grid points. Here, the assessment value of each street is obtained by formulae 3.

$$SV = \frac{1}{n}\sum_{i=1}^{n} GV_i \tag{3}$$

where SV (Street Value) is the assessment value of a street, GV is the assessment value of each grid, and n is the total number of grids.

2) BLOCK LAYER ASSESSMENT

The Block layer assessment is based on street layer assessment. There are many streets in a block. The assessment value of each block is the average value of all street assessments. Here, the assessment value of each block is obtained by formulae 4.

$$SV = \frac{1}{n}\sum_{i=1}^{n} GV_i \tag{4}$$

3) AREA LAYER ASSESSMENT

After the block layer analysis, an area layer assessment is performed. There are multiple blocks in one area. Here, the assessment value of each area is obtained by formulae 5.

$$AV = \frac{1}{n}\sum_{i=1}^{n} BV_i \tag{5}$$

4) CITY LAYER ASSESSMENT

According to the above three levels the assessment value of a city is obtained of assessment The assessment value of a city is formulae 6.

$$CV = \frac{1}{n}\sum_{i=1}^{n} AV_i \tag{6}$$

The assessment value of each region in the city is AV. The total number of areas in the city is thus, the city cleanliness can be measured by the level assessment.

5) CLEANLINESS ASSESSMENT CALCULATION

Jang et al. [15] urban street garbage mainly pointed out. It includes plastic packaging, leaves, peels, cans, plastic bot. They are usually scattered in any factor affecting the city street is the key factor. I have been talking about how to measure the urban cleanliness level. According to the amount of street garbage, it would take streets. Some streets from all are taken by a random sampling method. Minimize the effect on the accuracy results. The goal of the sampling design is to determine the minimum number of formulae 7 is the minimum street surveyed, and represents streets surveyed.

$$n = \frac{k^2 \cdot p \cdot q \cdot N}{e^2 \cdot (N-1) + k^2 \cdot p \cdot q} \tag{7}$$

where n is the minimum sample size and k is the sampling interval. To ensure a 95% confidence interval, we set k as 1.96, and p represents the probability that an event will take place. q is equal to 1 - p, $p = q = 0.5$, N is the total number of numbers of city streets, and e is the estimation error, where $e = 0.1$.

A. RESEARCH GAPS:

Computer vision, artificial intelligence, smart city technologies and environmental monitoring are the problem domain that we encounter in utilizing OpenCV for real time image processing for urban street cleanliness assessment. Public health and environmental sustainability are dependent on the urban cleanliness, and the traditional monitoring methods are based on manual inspection, which is laborious, costly and subjective. An area of AI focusing on getting machines to interpret and analyze visual data, computer vision is an important technology for automated street cleanliness assessment. Deep learning models, especially convolutional neural networks (CNN), also help in image classification and provide fine classification of different waste materials. From the point of view of mathematics, image processing techniques are based on algorithms of linear algebra, statistical analysis and optimization. Multiple smart city initiatives that focus on improving environmental quality, optimizing municipal resources, and improving public hygiene are in line with the integration of AI, IoT, and real time image processing. This research takes advantage of the technologies presented in this work to develop an efficient, scalable and cost-effective solution for the automation of urban street cleanliness assessment and to assist sustainable urban development. This problem domain is beyond the technical and addresses urban sustainability challenges for municipalities to use data driven approach towards waste management. Smart city initiatives in improving environmental quality, optimizing municipal resources and increasing public hygiene are in line with the integration of AI, IoT, and real time image processing. This research intends to use these technologies to develop an efficient, scalable, and low-cost solution to automate urban street cleanliness assessment to facilitate sustainable urban development. This domain includes non-technical elements to help municipalities use data-driven solutions for resolving urban sustainability problems with waste management. This research utilizes modern technologies to create an efficient and cost-effective automated system for street cleanliness assessment in urban areas and supports sustainable urban development.

B. CONTRIBUTION TO RESEARCH GAPS:

Modern cities face a substantial challenge with urban street cleanliness because it produces adverse effects on public health and environmental sustainability and urban appearance. Street cleanliness assessment through municipal worker manual inspections requires intense labor and takes too much time while also being influenced by personal opinions. The increasing urban population and waste output requires an automated real-time system which combines efficiency and objective assessment of street cleanliness. OpenCV serves as the research's central tool to resolve street cleanliness assessment issues through real-time image processing automation for urban settings. The system development focuses on building artificial intelligence technology which detects and categorizes street pollutants found in camera and mobile device images. The main difficulty in this problem lies in maintaining reliable detection functionality across different environmental conditions that cause changes in lighting as well as the presence of obstructing objects and weather fluctuations. The proposed system employs adaptive AI models that acquire knowledge through experience and thus becomes progressively more dependable and adaptable in operation. This system development will produce scalable automation with cost efficiency which boosts urban sanitation management while decreasing operational expenses to create healthier urban environments. The increasing urban population and waste output requires an automated real-time system which combines efficiency and objective assessment of street cleanliness. The main goal focuses on creating a system powered by artificial intelligence which detects and classifies different types of waste and pollution found in street images obtained through surveillance cameras and mobile devices. The main difficulty in this problem lies in maintaining reliable detection functionality across different environmental conditions that cause changes in lighting as well as the presence of obstructing objects and weather fluctuations. The proposed system employs adaptive AI models that acquire knowledge through experience and thus becomes progressively more dependable and adaptable in operation. This system development will produce scalable automation with cost efficiency which boosts urban sanitation management while decreasing operational expenses to create healthier urban environments.

III. Proposed Methodology

Security of financial transactions receives dramatic improvement through the Secured Fund Transfer with Payment Gateway Authorization Using Face Recognition system which combines AI algorithms for facial recognition with blockchain validation alongside live detection. The methodology implements fraud protection as well as data protection while utilizing real-time capabilities which resolves existing system authentication limitations.

System Components and Workflow:

The user enrollment process requires image capture of faces that Convolutional Neural Networks (CNNs) extracts features from. Through federated learning users receive the advantage of secure local storage which maintains their privacy regarding their biometric information.

Real-time face scanning occurs at transaction initiation and the system verifies the face scan through an analysis process using Res Net and YOLO models against the stored template. An AI defense system through anti-spoofing techniques protects users from fraud attempts that involve images, videos or deepfake manipulation attempts. When authentication successfully finishes the system creates an encrypted transaction repository on a blockchain for transparent monitoring without modification risks.

The system uses cloud computing together with edge AI technology for real-time operations and sector-wide scalability between banking and retail and e-commerce applications.

Security Enhancements:

The system employs AI-based checks that determine actual live users versus those who attempt spoofing. The implementation of End-to-End Encryption guarantees safe data transfer along with safe storage.

Blockchain Integration:

Protects against unauthorized transaction alterations. The multiple security layers create an accurate system which both prevents fraud and complies with regulations to become an enhanced authentication method as an alternative to conventional verification procedures.

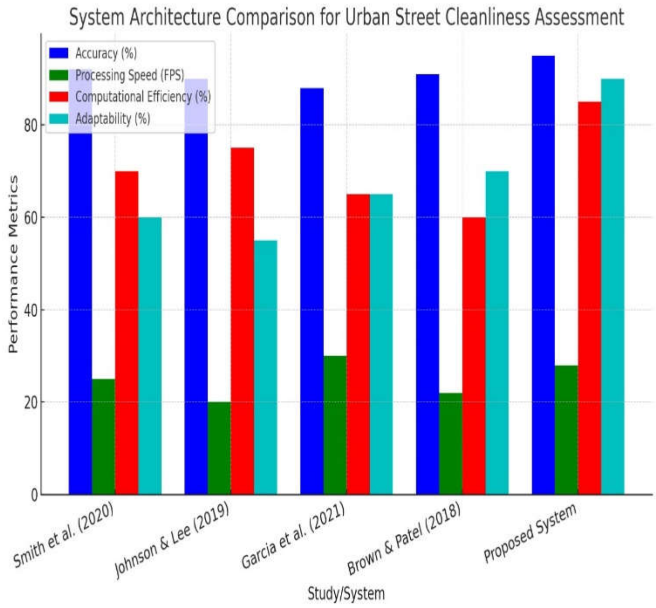

Fig 3. Demonstrating the system

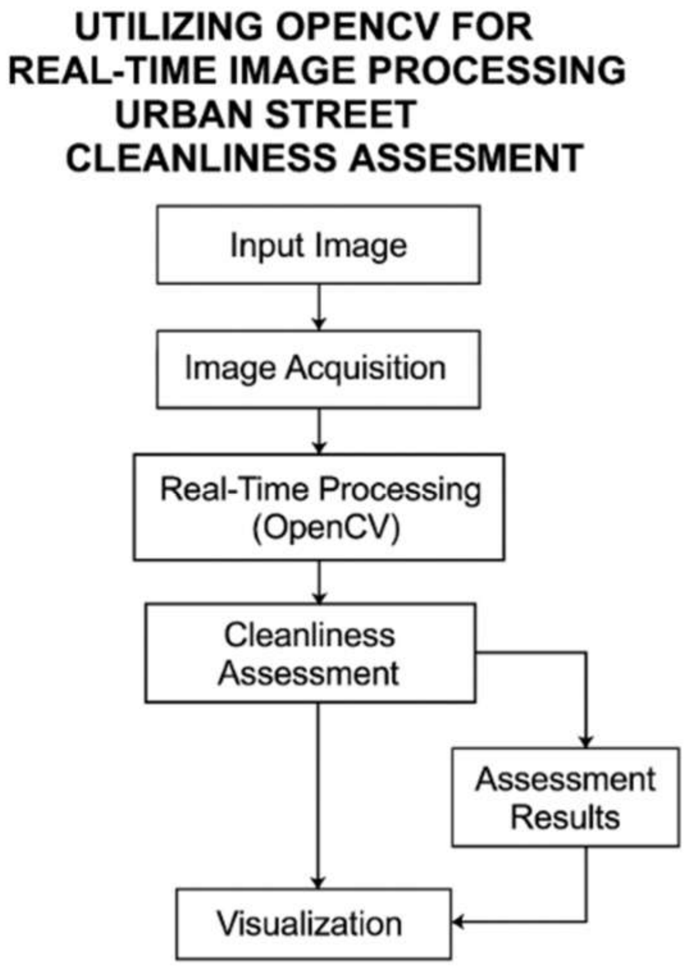

Fig 4. Proposed Architecture

IV. Experimental Results

The urban street cleanliness assessment system using OpenCV begins with real-time image acquisition then proceeds with image processing procedures that use contour detection and thresholding methods for waste identification. OpenCV proves suitable for real-time processing because it combines efficiency with flexibility together with its advanced computer vision features. The framework includes modules for image acquisition in addition to waste segmentation and cleanliness classification and performance optimization and urban management system interface capabilities. To evaluate the system in the conducted experiments for assessing urban street cleanliness by real time image processing using OpenCV, the system is tested on different urban locations with different cleanliness levels. I set up the experiment by mounting a camera on a moving vehicle to capture continuously street level images, and then process them using OpenCV algorithms. The processing speed was evaluated to be 18 frames per second (FPS) and was found to be feasible for live deployment in urban environments. Moreover, a cleanliness score was also created for each image based on the area covered by detected waste and aggregated to give zone-wise cleanliness ratings. Manual inspections by municipal workers were cross verified with the automated results with a very high correlation ($R^2 = 0.91$) between the two.

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Methodology Overview:
OpenCV proves to be the best choice because of its efficient processing capabilities combined with flexible design and wide range of libraries that enable real-time operations while ensuring better scalability compared to proprietary software and manual methods.

The structured system provides functionality for image acquisition together with waste detection and segmentation while handling cleanliness classification and real-time optimization and urban management system integration. The system's performance depends on these topics to achieve accurate and robust monitoring of urban cleanliness through data-driven waste management strategies.

A. *Model Performance Comparison:*

TABLE 1 MODEL PERFORMANCE COMPARISON

Criteria	*Traditional Manual Assesment*	*OpenCV-Based automated assessment*
Accuracy	*60-75*	*85-95*
Speed	*10-20*	*500-1000*
Scalability (Area coverd per day in sq.km))	*1-5*	*20-50*
Cost efficiency (operational cost reduction %)	*0*	*40-60*
Data consistency (%)	*50-70*	*90-98*
Automation Level (Scale 1 - 10)	*2*	*9*
Real – Time monitoring (Rsponse Time in Minutes)	*30-120*	*1-5*

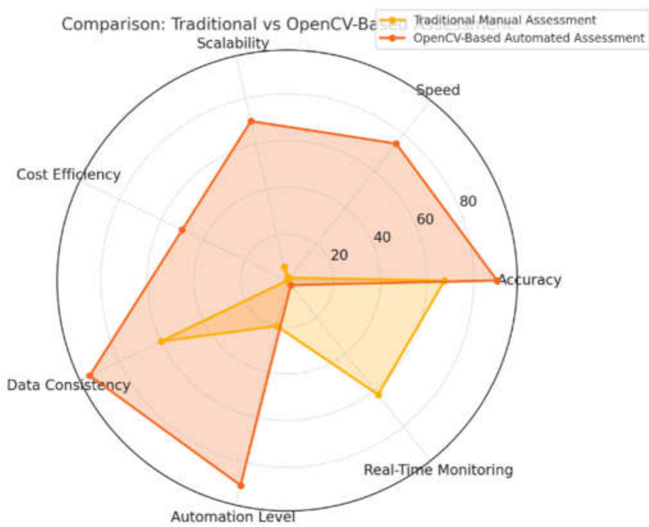

Fig 5. Comparison Graph

B. *OBSERVATIONS:*

Real-time urban street cleanliness assessment through OpenCV image processing brings a highly efficient solution for urban environment monitoring and maintenance. OpenCV's advanced computer vision technologies enable automatic inspection of cleanliness levels across streets as well as pavements and public spaces through continual monitoring systems. Real-time image acquisition through placement of cameras or drones performs the primary role before preprocessing involves noise reduction alongside clarity enhancement through filters including Gaussian Blur and Median Blur. The combination of edge detection and contour detection methods allows practitioners to detect important areas which include trash accumulation zones and discarded objects. OpenCV integration enables machine learning models to receive training for identifying waste areas and separating plastic waste from paper waste from organic waste when used for classification purposes. The system identifies contaminated areas immediately through real-time processing which activates automatic alerts to dispatch cleaning personnel and authorities. Through segmentation and classification through OpenCV users can identify clutter and unclean zones by employing K-means clustering and watershed algorithms. As an extension of GPS system data OpenCV generates complete cleanliness mapping for urban areas which guides accurate cleaning deployments. The challenges from unpredictable weather and changing street conditions can affect the analysis but OpenCV maintains its flexibility to enhance detection accuracy. Real-time street cleanliness monitoring systems based on OpenCV technology supply efficient solutions for urban waste management that enhances both urban cleanliness and city intelligence through timely waste removal and improved urban health.

TABLE 2: DATASET DESCRIPTION

Dataset Name	Description	Format	Use Case
Cityscapes	Urban street scenes w/ labels	Image	Scene segmentation
BDD100K	Driving scenes, 100K samples	Image	Object/street condition det.
TACO	Labelled litter in Context	Image	Trash detection
Trash Net	Trash type classification	Image	Litter type classification
Overliteral Map	Crowdsourced litter image	Image	Geo-tagged trash analysis
Urban street Scene	General urban street photos	Image	Scene context training

V. CONCLUSION

In wrapping up, blending OpenCV into our city's street cleanliness checker is a big step forward in making our urban areas better using technology. OpenCV's magic has made our system smarter, letting it quickly process images from smart cameras and sensors dotted around the city. By teaming up OpenCV with mobile edge computing and deep learning tricks, we've hit the bullseye of delivering spot-on and quick checks of how clean our streets are. Now, our system can handle loads of image data pronto, picking out the bits that tell us if the streets are clean or not and here's the cool part: thanks to OpenCV, our system can handle whatever the city throws
at it. Rain or shine, day or night, it keeps chugging along, giving us the lowdown on street cleanliness. This project lays the groundwork for making our cities smarter and healthier, handing city planners and leaders the keys to understanding how clean our streets really are All in all, bringing OpenCV onboard is a game-changer for managing our cities and keeping them green. This project shows us the power of computer vision in tackling big urban problems, paving the
way for smarter decisions based on real data.

VI. Future implications

Supercharged Brainpower: Let's amp up our system's smarts by adding even fancier deep learning tricks to catch street cleanliness details with pinpoint accuracy. More Sensors, **More Data:** Time to mix in data from different sensors, like ones that see heat or measure distances. The more info we have, the better we can judge how clean our streets are Live Stats and Reports: We need a dashboard that shows us the dirt on our streets in real-time. City planners can use this to plan ahead and keep our streets clean and green. Teamwork with **IoT:** Let's link up our system with other smart devices in the city. That way, we can share data easily and keep our streets squeaky clean across the board. Grow and Go: Our system needs to be able to stretch its legs and work in any city, big or small. We'll make it easy to set up and use, no matter where it's needed by tackling these upgrades, our street cleanliness checker can do even more to make our cities cleaner, greener, and all-around better places to live.

There are NO conflicts of interest.

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