Litterlens – A deep learning based urban waste detection tool

By

Irza Mahmood

(Registration No: 00000401222)

Department of Sciences

School of Interdisciplinary Engineering & Sciences

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

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Irza Mahmood

(Registration No: 00000401222)

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School of Interdisciplinary Engineering & Sciences

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

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Signature with stamp: ____________

DR. MUHAMMAD T...
ASSOCIATE PROF...
School of Interdisciplinary E...
& Sciences (SINES)
NUST, SECTOR H-12, ISLAMABAD

Name of Supervisor: Dr. Muhammad Tariq Saeed

Date: 25-07-2024

Signature of HoD with stamp: ____________

Dr. Fouzia Malik
HoD Sciences
Professor
SINES NUST, Sector H-12
Islamabad

Date: 29-7-2024

Countersign by

Signature (Dean/Principal): ____________

Dr. SYED IRTIZA ALI SHAH
Principal & Dean
SINES - NUST, Sector H-12
Islamabad

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DEDICATION

Dedicated to my beloved parents, my siblings, my dear friends Hafsa and Mahnoor, and my partner Abdullah.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

CNN	Convolutional Neural Network
D-CNN	Deep CNN
YOLO	You Only Look Once
VGG	Visual Geometry Group
SDG	Sustainable Development Goal
YAML	Yet Another Markup Language
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
GUI	Graphical User Interface

ABSTRACT

The increase in solid waste pollution and its accumulation due to population expansion is becoming a significant threat in developing countries like Pakistan. Pakistan ranks as the 5th most populated country in the world and produces almost 49.6 million tons of solid waste annually, which has been increasing at the rate of 2.4% each year. Efficient solid waste identification and collection strategies still need to be improved in Pakistan in contrast to conventional methods, which result in inadequate allocation of resources to areas in need and ineffective waste collection operations. This research bridges the gap by providing a deep learning-based solution for the efficient identification of areas with high waste volume by developing a data-driven tool that promotes community involvement to apply a customized waste management approach in Pakistan. A local dataset of 3693 waste images was collected from different cities in Pakistan to train the deep learning models, as no specialized waste dataset was available for Pakistan. This study used three deep learning models, i.e. Deep CNN, You Only Look Once (YOLO) v8 classification model, and Visual Geometry Group (VGG)-19. Overall, all models achieved more than 90% accuracy when trained at 20 and 50 epochs. However, among these networks, YOLOv8 was the highest-performing model with an accuracy of 99.5% at 50 epochs. Furthermore, a functional prototype for the tool was created using the Python Tkinter package, which integrated the best-performing model, allowed the upload of images, and provided classification results in an inference time of under 1 second. Hence, this deep learning-based solution is an efficient approach to waste management in Pakistan and has the potential to be implemented with further improvements along the way.

Keywords: Solid Waste, Image classification, Deep learning, Deep CNN, YOLOv8, VGG-19.

1. INTRODUCTION

Pakistan, an emerging nation in South Asia, is confronted with an escalating issue of urban garbage management as a result of its expanding population and swift urbanization [1]. Pakistan, with a population of around 241 million as of 2023, ranks as the fifth most populated nation globally [2]. The swift and exponential growth of the population, along with unplanned urbanization, has led to an exponential increase in municipal solid waste output. This condition poses a serious threat to the ecology and public health in the country. As per a report by World Bank, in 2017, Pakistan generated almost 30 million tons of municipal solid waste (MSW), or 82,000 tons per day [3]. Pakistan produces almost 49.6 million tons of solid waste per year, and this amount is expected to increase by over 2.4% annually [4] [5]. Most of this solid waste is discarded by means of open incineration, dumping, or burial in vacant spaces, resulting in significant environmental deterioration and public health issues. Poor waste management has led to the pollution of soil, air, and water resources, which has in turn caused the spread of diseases transmitted by vectors and the decline in the general quality of life for the people of Pakistan [6].

1.1 Current waste management in Pakistan

The majority of Pakistan's current waste management initiatives are inadequate and ineffective. Local and municipal governments have to oversee the collection and removal of garbage. However, they regularly have difficulties managing the increasing volume of solid waste due to limited resources, inadequate infrastructure, and inadequate technical capability [7] [8]. Major metropolitan regions have garbage collection rates ranging from 60% to 70%, which leaves a significant amount of trash uncollected and improperly disposed of [9]. This issue is made worse by the lack of suitable garbage disposal facilities, as just a few cities, including Karachi and Lahore, have sanitary landfills [5]. Scavengers and trash pickers are part of the informal sector, which is vital to recycling and recovering valuable items from the waste stream. However, these informal techniques can present risks and do not follow proper safety procedures, exposing workers to environmental and health risks [10]. These unofficial methods have become widely used because of the absence of a comprehensive and integrated waste management system, yet they are insufficient to address Pakistan's mounting garbage problem.

1.2 Utilizing deep learning approach for waste management

Establishing a thorough and evidence-based waste management system is essential for tackling this rising problem. The absence of a dependable and comprehensive dataset on urban garbage in Pakistan has posed a substantial obstacle to executing efficient waste management techniques. The lack of comprehensive data regarding solid waste composition, distribution, and attributes makes it difficult to perform focused efforts and distribute resources efficiently. One of the objectives of this research is to fill this void by generating a complete dataset of waste photos collected from different areas in Pakistan. This project aims to use deep learning techniques to create an effective image classification model capable of accurately identifying solid waste in images. This dataset and the accompanying deep learning model will be useful assets for researchers, policymakers, and waste management authorities in Pakistan. They will be empowered to make well-informed decisions and execute more efficient waste management policies.

As part of this project, a web tool called Litterlens will be developed, enabling individuals to post photographs of garbage they come across in their local neighbourhoods together with geographical data. This information will be compiled and analysed to give a real-time, data-driven knowledge of garbage distribution and trends across various locations. With access to this data, waste management authorities can pinpoint problem regions, allocate resources more effectively, and adopt customized solutions to alleviate trash. The Litterlens project intends to encourage civic engagement and responsible environmental behavior by enabling individuals to actively participate in waste management by integrating deep learning technologies with an easily navigable web platform. This strategy will increase public awareness of the value of appropriate waste management while increasing garbage collection and disposal efficiency. In addition, the Litterlens initiative will help Pakistan achieve its larger objective of developing smart and sustainable cities. The project will offer a thorough and data-driven framework for waste management, using cutting-edge technologies like deep learning and geospatial data. This will ultimately result in a cleaner, healthier, and more livable urban environment.

1.3 Problem Statement

The absence of a deep learning-based waste detection method in Pakistan is a substantial obstacle to the efficient handling of solid waste. Underdeveloped countries, like Pakistan, encounter difficulties in implementing effective methods for collecting solid waste, leading to environmental pollution and risks to public health. The absence of an effective cleaning strategy worsens the problem, impeding efforts to tackle the more difficult waste management dilemma. The process of detecting and classifying waste, which is made more challenging by the varied composition of household waste, exacerbates the complexity of waste management in urban areas. Inadequate allocation of resources for waste disposal, ineffective waste collection operations, and manual classification result from the absence of automated garbage detection systems. The presence of this knowledge gap in waste management approaches highlights the urgent need for advanced solutions, including deep learning-based urban waste detection systems, to enhance waste collection efficiency, improve waste classification accuracy, and advance waste management effectiveness as a whole. To tackle these challenges, it is imperative to embrace a comprehensive approach that incorporates cutting-edge technologies, data-driven methodologies, and community involvement to formulate sustainable and efficient waste management strategies customized to the unique requirements of developing nations such as Pakistan.

1.4 Objectives

This research aims to achieve the following objectives:

- Creation of a solid waste images dataset to train the deep learning model for detection.
- Development and training of a deep learning-based model for accurate detection of sites with high accumulation of garbage.
- Creation of an intuitive and innovative web-based tool for efficient community engagement and data collection.

1.5 Relevance to national needs

In light of the statistics of increasing solid waste pollution and limitations of waste collection discussed in Section 1.1, it is evident that current research in the sector of urban waste management is required to accomplish the following:

- By utilizing a sophisticated deep learning model, it is possible to achieve efficient and automatic garbage recognition.
- This system offers a cost-effective answer to the difficulties associated with urban waste management.
- It provides assistance in making decisions based on data in order to develop strategies and plans for urban cleanup.
- An effective method of identifying garbage hotspots will contribute to the improvement of cleanliness in society.

As a result of this study, the project seeks to optimize waste management in urban areas by developing a comprehensive dataset of garbage images and integrating it into a web-based platform. This integration intends to improve the effectiveness of waste identification, collection, disposal, and resource allocation. This can result in a decrease in the detrimental environmental effects of metropolitan areas. Ultimately, this will help us accomplish United Nation's Sustainable Development Goal (SDG) 11 - *Sustainable cities and communities.* Enhanced waste management strategies can aid in climate action by diminishing greenhouse gas emissions from waste disposal and fostering a more circular economy. The project's emphasis on utilizing data to inform decision-making and actively involving citizens can also contribute to local and national endeavors aimed at tackling the obstacles posed by climate change, as described in Sustainable Development Goal 13 – *Climate action.* This study also supports the implementation of measures to reduce solid waste pollution and promote sustainable waste management practices, which can have positive effects on terrestrial ecosystems and biodiversity. The project aims to enhance the preservation and rehabilitation of terrestrial ecosystems by mitigating the inappropriate disposal of garbage and advocating for ethical waste management, as outlined in Sustainable Development Goal 15 – *Life on land*. Furthermore, the study highlights the significance of community involvement and cooperation among residents, local government, and waste management participants. The project aims to enhance waste management efforts in Pakistan by implementing a web-based platform that enables citizens to report waste issues. This approach fosters partnerships and multi-stakeholder cooperation, ultimately improving the effectiveness and sustainability of waste management, which aligns with SDG 17 – *Partnerships for the goals*.

1.6 Thesis Structure

This research thesis adopts a thorough structure to achieve the aforementioned aims in section 1.4. Chapter 2 covers a literature review to assess the extent of research on waste management in Pakistan and deep learning-based waste detection and highlight possible research gaps. Chapter 3 describes the study's research methods, followed by Chapter 4, which highlights the results. Finally, Chapter 5 finishes the thesis with a review of the findings, acknowledgments of shortcomings, and recommendations for how to overcome them.

2. LITERATURE REVIEW

In recent years, there have been various studies worldwide presenting the implementation of machine learning and deep learning algorithms for the purpose of waste management strategies. However, the research regarding utilization of such techniques for waste management in Pakistan is limited and neglected due to absence of a specialized local waste dataset. In the following section, we have studied the existing literature related to different waste management practices in Pakistan and other deep learning models used worldwide.

2.1 Waste management approaches in Pakistan

The paper by Agha Muhammad Furqan Durrani et al. introduces an innovative system for waste management, incorporating an electronic waste detection device and a central control unit. An infrared sensor for waste level measurement, a GPS unit for location tracking, an Arduino board with a microprocessor, and a GSM module for real-time communication are all included in the research technique. Data on trash level is received by the central control unit by a GSM module, and it is then sent to computer software for management and monitoring. The research highlights the significance of automated waste management systems in enhancing the effectiveness of waste collection and disposal procedures. Results illustrate how well the AWCMS prototype was implemented, displaying position tracking, real-time waste monitoring, and status updates in an intuitive graphical user interface. The sophisticated operation of the system facilitates prompt waste collection and transportation, hence augmenting the overall efficiency of waste management. In order to address the risks connected with poor waste disposal procedures, the study emphasizes the importance of automated waste management solutions [11].

Another study by Hasan, Mohammad Kamrul, et al. describes a comprehensive smart litter management system that blends IoT-based monitoring with deep learning waste classification. The presented system contains two major components: 1) an IoT-based smart waste bin with sensors that continually monitor garbage levels and composition in real time; and 2) a deep learning-based waste classification module that uses Convolutional Neural Networks (CNNs) to recognize various waste categories such as metal, glass, paper, plastic, and so on. The authors tested multiple CNN architectures, including ResNet, VGG16, MobileNet, DenseNet, and Inception-v4, and attained test accuracies of up to 97% using the DenseNet-169 model after 120 training epochs. The IoT component sends waste data to a central system, which optimizes waste collection routes and schedules. The deep learning component allows for effective waste sorting and recycling at the waste collecting plant. The researchers point out that the current prototype only handles a limited number of waste categories, and that increasing the dataset size could improve classification performance in future work. Overall, the article describes a full smart trash management solution that uses IoT and deep learning to enable effective and sustainable waste management in smart cities [12].

The paper by Wilayat Ali Khan et al. introduces an innovative approach to solid waste management using geotagging and severity ranking. The research methodology involves leveraging a mobile application for users to report waste type and weight, integrating GIS for mapping garbage data, and determining the severity of waste accumulation in specific locations. The study emphasizes the importance of socializing the garbage identification process and utilizing geographic data to address solid waste management challenges effectively. The results show the successful implementation of the proposed mechanism, enabling users to register garbage data and determine the severity level of waste in different geographical areas. The interactive dashboard visualizes garbage severity, risk counts, garbage types, and average quantities, providing valuable insights for municipal administration. However, a research gap exists concerning the scalability and adaptability of the mechanism in the context of Pakistan. The paper lacks a detailed exploration of creating a comprehensive waste dataset specific to Pakistan and training deep learning models for urban waste detection, highlighting the need for further research to tailor the approach to the unique waste management landscape of Pakistan [13].

A research by M. Saad et al. presents an innovative approach to address the obstacles of solid waste management in urban areas. The research methodology involves the integration of Distributed Ledger Technology (DLT), Blockchain, Internet of Things (IoT), and

Vehicle-to-Everything (V2X) communication to develop a comprehensive Blockchain-enabled Vehicular Ad-Hoc Network (VANET) for smart solid waste management. The proposed system utilizes Ultra-High Frequency (UHF) technology for real-time surveillance of waste bin levels and vehicle identification. IoT devices installed on waste collection vehicles transmit data to the Blockchain-enabled VANET, enabling efficient route optimization and timely waste collection. The system also incorporates geo-fencing techniques to create virtual boundaries for waste collection sites and weighing stations. The results demonstrate the successful execution of the Blockchain-enabled VANET system, providing real-time tracking of waste collection vehicles, identification of waste bins, and integration with weighing scales. The system's decentralized architecture and use of Blockchain technology ensure secure and reliable data transmission, addressing the limitations of centralized waste management systems. The authors also discuss the economic feasibility and quality of the proposed solution, highlighting its potential for adoption in developing countries with limited resources for solid waste management [14].

One paper by Sahar Idwan et al. proposes an agent-based approach to optimize solid waste collection in smart cities. The research methodology involves equipping dumpsters with HC-SR04 ultrasonic sensors to detect waste levels and communicate this information to a central control station. The control station then assigns tasks to waste collection trucks, which use a modified Dijkstra's algorithm to plan optimized routes based on the real-time dumpster fill levels. The results demonstrate significant reductions in the total distance covered by the garbage collection trucks compared to a traditional dumpster system. In the worst-case scenario, the distance was reduced by 88%, while in a more realistic scenario, the distance was reduced by 30%. This translates to substantial savings in fuel consumption and service time for municipal authorities. The study highlights the potential of wireless sensor networks and intelligent routing algorithms to enhance the efficiency of solid waste management in smart cities, a crucial consideration for developing countries like Pakistan facing waste management challenges [15].

2.2 Deep learning approaches for waste detection

Various deep learning architectures and machine learning algorithms have presented an opportunity to streamline the automation of garbage detection throughout the world. With the help of several existing datasets consisting of solid waste images e.g., Trashnet, TRWD, TACO [16], UAVVaste, AquaTrash [17], Litter Map etc., a garbage detection model can be trained to detect solid waste from images with high accuracy [18].

Automated detection of garbage has been achieved at various levels by incorporation of different deep learning models, which is further utilized in waste segregation and collection. Deep learning architectures like AlexNet [19], ResNet [20], You Only Look Once-v3 (YOLO-v3) [21], YOLO-v5 [22], Convolutional Neural Network (CNN) [23], EfficientDet-D2 [18], and GarbNet [24]etc.

The level of research carried out on utilizing different deep learning models for waste detection through images is growing rapidly. However, developing a tool and collecting data for the purpose of improving urban planning is a fairly new approach. Numerous studies have been undertaken in recent years that have shown promising results for waste detection by using different object detection models developed through deep learning.

A recent study published in MDPI journal [21] proposed waste segregation using the YOLOv3 algorithm. The YOLOv3 algorithm is a deep learning algorithm that is able to identify objects in pictures. The YOLOv3 algorithm was applied on a dataset of 6437 images of urban waste products. The dataset consisted of six different classes of waste items: glass, cardboard, metal, plastic, paper, and organic waste. After assessing the model's performance on a test set, the authors found that the model's average precision was 90% which is a high accuracy for waste segregation. The study concludes that the YOLOv3 algorithm was able to achieve a high accuracy in detecting waste items. It is a promising approach for waste segregation and is able to achieve a high accuracy in detecting waste items and can do so in near real-time.

Another study showing promising results of YOLO for waste detection investigates real-time object detection to identify multiple objects in a single picture [25]. The dataset used are Trashnet and another dataset created with domestic waste images from Taiwan only, called Taiwan Recycled Waste Database (TRWD). The images in the TRWD dataset are labeled with the type of waste that is present in the image. The model was trained on both datasets and tested to detect domestic waste in Taiwan. The TRWD-trained YOLO showed a higher accuracy in detecting domestic waste than the Trashnet-trained YOLO. This study concluded that the YOLO algorithm was able to obtain a high accuracy in detecting waste items. Additionally, the development of a country specific solid waste images dataset is vital to increase the detection accuracy and further help in utilizing that model in waste sorting.

One other study suggests an unmanned aerial vehicle (UAV)-based intelligent waste identification system employing deep learning [26]. The system uses two convolutional neural network (CNN) models to detect and classify different categories of garbage. The first CNN model is used to identify the presence of garbage in an image, while the second CNN model is used to classify the type of waste material. The dataset used to train the CNN models was collected by a quadcopter with a camera to take pictures of waste areas. Initially around 2000 instances were collected, out of which 1000 instances belonged to clean areas and the other 1000 images displayed garbage. The results of the study showed that the CNN models were able to obtain a high accuracy in detecting and classifying garbage. The first CNN model was able to attain an accuracy of 94% in detecting garbage, while the second CNN model was able to attain an accuracy of 90% in classifying garbage.

The work published in the Journal of Physics [27], discusses a novel strategy that suggests an autonomous garbage identification system based on narrowband internet of things (NB-IoT) and deep learning. The system uses the YOLOv2 object detection model to detect garbage in images captured by a camera. The dataset consists of 570 pictures of urban data containing garbage, split into various sets, including 300 instances in training set, 120 instances in validation set, and 150 pictures in test set. The results display the effectiveness of the proposed system, showcasing its potential in automating garbage detection processes and contributing to smarter waste management in urban environments. The integration of NB-IoT ensures efficient and seamless data transmission, enhancing the overall performance and scalability of the system.

One further recent study published in Elsevier journal utilized an EfficientDet-D2 algorithm for waste detection [18]. The EfficientDet-D2 algorithm is a deep learning algorithm that can be used to identify objects in pictures. For this research, about 11 different available datasets were merged to form a detect-waste dataset used for training, which contained images that originate from three primary environmental categories: indoor, outdoor (urban and natural), and underwater. The images were labeled with the type of waste that is present in the image. The study's findings demonstrated that the EfficientDet-D2 network, which has fewer parameters and uses less processing power, produced the best evaluation results. The research concluded that the EfficientDet-D2 algorithm is a promising approach for waste detection in both urban and natural settings, making it a potential candidate for use in smart waste management systems.

In another publication [28], the authors researched a deep learning approach for autonomous garbage detection. The authors used the Faster R-CNN open-source framework with region proposal network and ResNet network algorithm to train a model for garbage detection. Additionally, they suggested a data augmentation and fusion plan to enhance the method's accuracy. The dataset utilized in this research consisted of 816 pictures of garbage. These were divided into a training set of 596 instances and a test set of 220 instances. The authors evaluated the performance of their model on the test set. They achieved a detection accuracy of 89%. The results showed that the suggested method was effective for autonomous garbage detection. The data fusion strategy proposed in the paper is able to detect smaller regions of garbage accurately. However, the speed and performance of real-time detection warrants more research and optimization. Overall, the paper presents a promising approach for automatic garbage detection. The proposed method is accurate and can be used to improve the cleanliness of urban areas.

Another significant paper [29] proposed a smartphone app called SpotGarbage that uses deep learning to identify garbage in pictures. The application makes use of the convolutional neural network (CNN) architecture known as AlexNet, which was pre-trained using the ImageNet dataset. The dataset called Garbage in Images (GINI) dataset contains over 2,500 images of garbage which has been used for training and fine-tuning the CNN and consists of a diverse collection of images containing various types of garbage items, such as plastic bottles, wrappers, cans, and more, commonly found in different environmental settings. The dataset is meticulously labeled to ensure the model learns to accurately identify and classify different waste objects. The results of the study demonstarted that the SpotGarbage app was able to attain an accuracy of 87.69% in detecting garbage. The app demonstrates remarkable accuracy and reliability in detecting different waste items, giving users the tools they need to take an active role in trash management initiatives and help build cleaner, more sustainable communities.

These studies show that utilizing deep learning architectures to detect solid waste from images with a high accuracy, and collecting these images through a tool from citizens to develop an extensive database helpful for urban planning and smart waste management has a promising potential and needs to be investigated.

2.3 Research Gaps

Table 2.1: Summary of datasets, results and limitations of relevant literature

Author	Dataset	Results	Limitations
Ying Wang, Xu Zhang	Acquired their own dataset from sanitation department. (816 images)	Achieved the speed of 6 seconds per image. Detection accuracy 0.89.	Not generalizable for Pakistan. Need to reduce detection time with high precision. No tool was designed.
Majchrowska, Sylwia, et al.	Combined 10 existing datasets to create 2 datasets of their own. Waste Pictures, Open Litter Map, Trashnet, Extended TACO, Wade-AI, UAVVaste, Trash-ICRA, TrashCan,	Average precision of waste detection ranged from 28.0% for Mask R-CNN with to 65.5% for EfficientDet-D2. The classification of waste resulted in about 75% accuracy	Not generalizable for Pakistan. An improvement in the model accuracy is required for better performance. No web-tool or application designed on the model.

	Drinking Waste, MJU Waste, Places.	using EfficientNet-B2 model.	
Verma, Vishal, et al.	Dataset created by images collected by a UAV and applied data augmentation.	One of the proposed deep CNN models showed an accuracy of 94%.	Deployment of drones can be very expensive and risky. Cannot be applied with same efficiency for Pakistan. No tool or application designed on the model.
Mao, Wei-Lung, et al.	Trashnet and Taiwan Recycled Waste Database (TRWD)	Demonstrated that each region should develop their own waste dataset for proper detection. YOLO-v3 achieved the highest mAP@0.5 of 92.12% with TRWD dataset and 81.36% with Trashnet dataset.	The model was trained by a single object dataset and hence was not efficient in detecting waste in bulk. Not generalizable for Pakistan. No web-tool or application designed on the model
Kumar, Saurav, et al.	Self-made dataset consisting of 7826 images.	Comparison between average precision of detection for YOLOv3 and YOLOv3-tiny resulting in mAP 94.99% and 51.95% respectively.	Inaccurate detection for images containing waste in bulk. Not generalizable for Pakistan. No web-tool or application designed on the model.
Mittal, Gaurav, et al.	Garbage In Images (GINI)	Garbnet model without normalization layers achieved an accuracy of 87.69% and 1.5s of detection time.	The accuracy of the model needs to be improved. The model was unable to detect images with

		Development of a tool called SpotGarbage.	scattered waste or oddly shaped objects. Not generalizable for Pakistan.

Hence after conducting the literature review, we identified a few gaps in the existing literature (as shown in Table 2.1: Summary of datasets, results and limitations of relevant literature), which would be countered by our research. One of these gaps included the absence of a waste image dataset based in Pakistan to efficiently train a model which would perform accurately to identify the waste materials found in our community, and the other gap is the lack of a tool where waste can be reported by the citizens. Both of these gaps have been addressed by our research and the details are mentioned in the following sections.

3. METHODOLOGY

This study followed the conventional deep learning methodology of data collection, data preprocessing, model training and inference and evaluation of the trained models. A primary dataset was collected by collecting the images of garbage and the collected images were preprocessed and annotated for the purpose of model training. This data is then used to train three different neural networks for the purpose of classification of images. Lastly, each model was evaluated based on their performance matrices and the highest performing model was selected for further optimization to achieve greatest accuracy and involved in prototype development. A summarized view of the methodology can be seen in Figure 3.1.

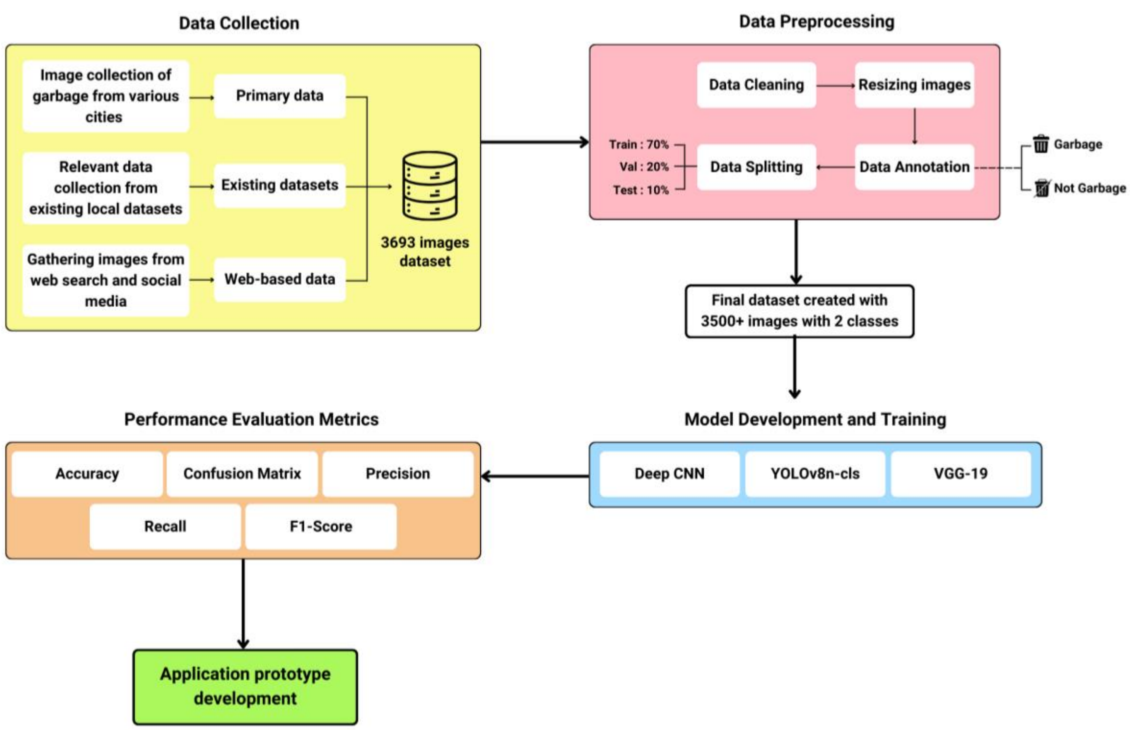


Figure 3.1: Flowchart of proposed methodology

3.1 Data Collection

For this study, it was found that there existed no appropriate dataset containing images of garbage in Pakistan. Various datasets exist containing images of solid waste, but no such dataset was found to be collected from Pakistan, which was required for this study. Hence, a primary dataset was collected of 3693 images consisting of 1847 images of garbage and 1846 images containing no garbage. Images were collected for both classes for the model to be trained and classify images efficiently.

Firstly, to create the primary dataset, images were taken in different cities from a personal camera by the author. The cities included in this data collection were Islamabad, Rawalpindi, Karachi, Lahore, Sialkot, Quetta, Multan, and Mirpur AJK (as visualized in Figure 3.2: Cities targeted for local data collection). Secondly, we went through different datasets based in Pakistan to gather any relevant images for this study. Finally, the research employed a multi-pronged approach to image acquisition, utilizing both targeted web searches and social media scraping techniques.

Figure 3.2: Cities targeted for local data collection

3.2 Data preprocessing

After the collection of image data, the images were preprocessed by cleaning, which included elimination of blurry photos, resizing of images and orienting. This step was performed manually by viewing each image and was necessary as it makes sure all the images in the dataset have a uniform quality for model training. After cleaning and resizing, the data was uploaded on Roboflow and annotated into two classes of “Garbage” and “Not Garbage”. Following the image annotation process, the data was segmented into three distinct sets for training, validation, and testing, adhering to the following pre-defined allocation ratios:

- Training set: 70% of data used for training of the models.
- Validation set: 20% of the data used to validate the models.
- Test set: 10% of the data applied for testing the performance of the models.

Data splitting concludes the phase of data preprocessing, and the images were ready to be used for model training purposes.

3.3 Model Training

Once the data has been annotated and split into train, validation, and test set, it is ready to be used for model training. For this research, we have selected three different neural networks for classification to analyze which network will yield the best results. The three classification models employed include:

1. Deep CNN
2. YOLOv8 Classification
3. VGG-19 Classification

Since we are utilizing these networks for binary classification as we have 2 classes in our data, transfer learning is applied for pre-trained models such as YOLOv8 and VGG-19, which have been trained on large datasets e.g. ImageNet, MNIST etc [30]., to extract valuable features and knowledge. Transfer learning is a machine learning technique that involves repurposing a pre-trained model for a different but related task [31]. This method capitalizes on the knowledge gained from previous tasks, thereby improving accuracy and efficiency in training models for new tasks [32].

3.3.1 Deep CNN

The deep convolutional neural network (CNN) model we developed is a robust and effective architecture for binary image classification tasks. The model comprises of several key components, including convolutional layers, max pooling layers, dropout layers, and fully connected layers, which work jointly to extract and classify features from input image data.

The 2 convolutional layers are responsible for retrieving features from the input images, while the max pooling layers minimize the spatial dimensions of the feature maps, thereby decreasing the computational complexity and preventing overfitting. We used the 16, and 32 filters in the convolutional layers allowing the learning of increasingly complex features as the depth of the network advances, contributing to the model's strong performance in binary classification tasks [33]. Another aspect of the model is the inclusion of a dropout layer with 0.2 rate, which, during training, randomly sets a portion of the input units to 0 in order to aid prevent overfitting, thereby promoting the model's generalization ability [34]. The use of a flatten layer after the convolutional and max pooling layers enables the conversion of the 2D feature maps into a 1D vector, which can be fed into the fully connected layers for classification [33].

The final fully connected layer, with a single neuron and a sigmoid activation function, is designed specifically for binary classification tasks, making it well-suited for the data. The sigmoid activation function ensures that the output lies between the probability values of 0 and 1, which can be interpreted as the likelihood of the input image belonging to the positive class [35].

Figure 3.3: Architecture of deep CNN model highlights the architecture of deep CNN model, which includes convolutional layers, max pooling layers, dropout layers, and fully connected layers, is planned to extract and classify features effectively, making it a suitable choice for binary image classification tasks. The model's robust performance can be attributed to its carefully designed architecture and the use of appropriate activation

functions, which contribute to its strong generalization ability and suitability for binary classification tasks.

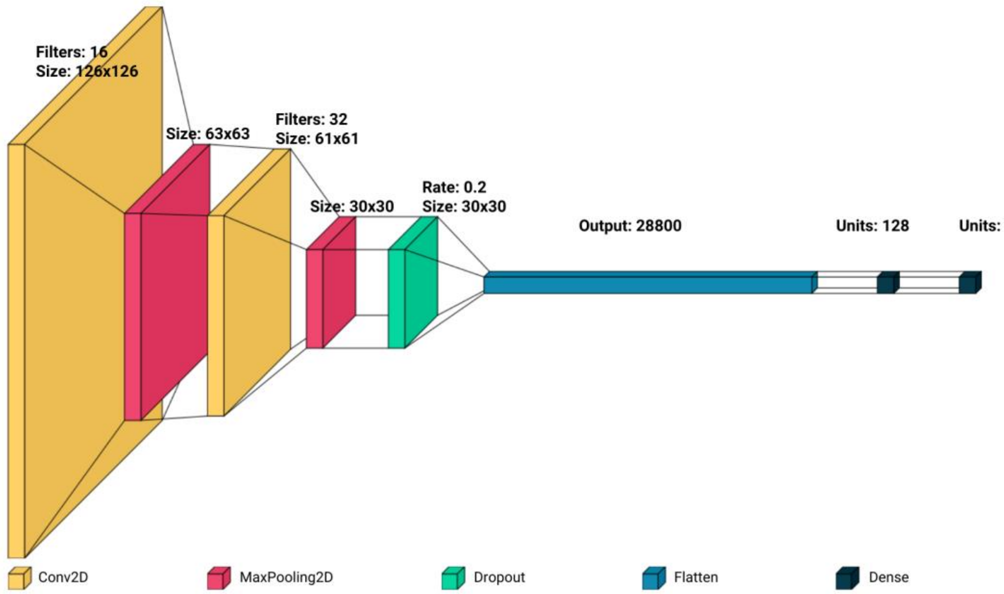


Figure 3.3: Architecture of deep CNN model

3.3.2 YOLO (You Only Look Once) V8 Classification Model

The YOLOv8 (You Only Look Once) classification model, an innovative object detection and classification algorithm developed by Ultralytics, is renowned for its precision and efficiency in image analysis tasks. Adaptive training is used by YOLOv8 to balance the loss function and provide optimum the learning rate during training, improving model's performance. The architecture of YOLOv8 comprises three main parts: the backbone, neck and head, consisting of multiple layers, including convolutional layers that extract features from input instances, pooling layers that downsample feature maps, and fully connected layers that perform classification based on extracted features [36], [37] (as shown in Figure 3.4). The neurons within these layers process information through weighted connections, making it possible for the model to learn and predict. Deploying YOLOv8 on a custom dataset involves structuring the dataset appropriately, training the model with the custom data, validating its performance, and exporting it for deployment. Adapting YOLOv8 for binary image classification necessitates modifying the final layers to output class probabilities, adjusting the network architecture, and retraining the model with the custom dataset to ensure accurate classification results. This is done by creating a YAML (Yet Another Markup Language) file to specify the data paths, number of classes and names of classes for classification [38].

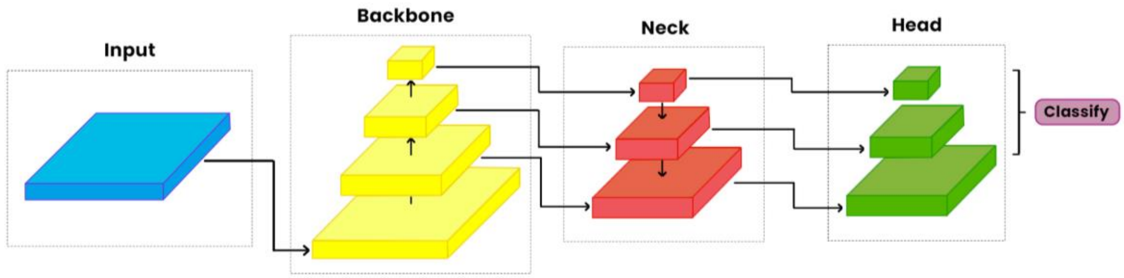


Figure 3.4: Architecture of YOLOv8 model [39]

3.3.3 VGG-19

The VGG-19 classification model, introduced by Karen Simonyan and Andrew Zisserman in 2014, is a renowned deep convolutional neural network (CNN) that has demonstrated impressive performance in image classification tasks. The architecture of VGG-19 comprises 19 layers, including 16 convolutional layers, 5 max pooling layers, and 3 fully connected layers (as visualized in Figure 3.5). The max-pooling layers interspersed between the convolutional layers downsample the data that aids in reducing computational complexity and mitigating overfitting. The fully connected layers perform the final classification based on the extracted features. The VGG-19 architecture is characterized by its simplicity, as it primarily utilizes 3x3 filters and 2x2 pooling layers, which contribute to its robust feature extraction capabilities. The model's depth enables it to learn intricate patterns and expressions inside pictures, making it highly effective for various image classification tasks [40], [41]. Although originally the model was designed for multi-class problems, we modified the model for binary classification by fine-tuning the final layers.

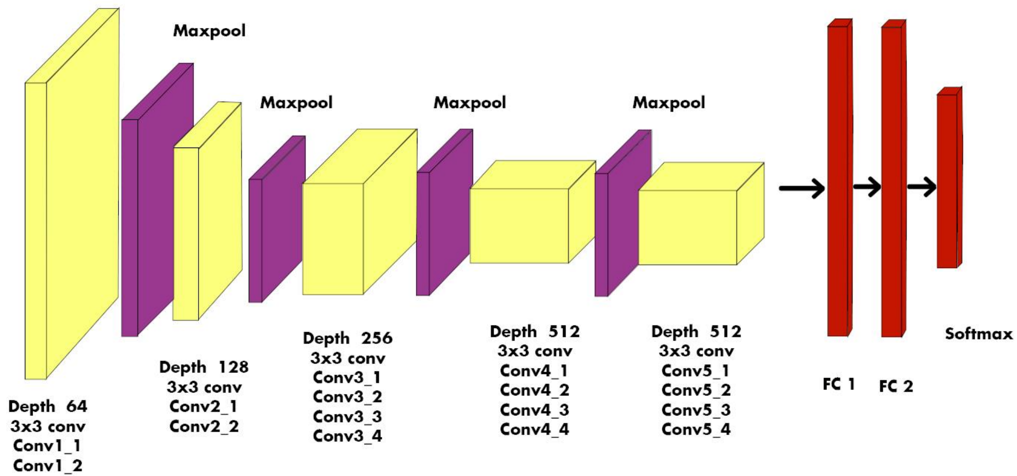


Figure 3.5: Architecture of VGG-19 model [46]

3.4 Performance Evaluation Metrics

To evaluate the performance of the selected models, several evaluation metrics are investigated in both the training and testing stages. In these stages, the targets labelled in the dataset are compared with the classification labels provided by the model. These metrics allow a thorough analysis of the model's performance by revealing how well they can classify the data. The strengths and limitations of the models can be determined by comparing the predicted labels with the ground truth labels, which can help with future optimizations and improvements. Evaluating them across various metrics ensures that the models solve the required classification tasks effectively. The following metrics have been selected to provide an in-depth analysis of the performance of each classification model.

3.4.1 Accuracy

Accuracy is an important measure which defines how closely the predicted labels align with the actual labels of the data. It is a basic evaluation method and is calculated by dividing the number of correct predictions by the total number of predictions made.

$$Accuracy = \frac{\textbf{Number of Correct Predictons}}{\textbf{Number of Total Predictions}} \tag{3.1}$$

3.4.2 Confusion Matrix

A confusion matrix summarizes the performance of a model by comparing the actual class labels in the dataset with the predicted class labels by the model in a tabular form (Table 3.1). In classification problems, confusion matrix is a valuable measure for evaluation as it provides insights into the type of error model is making and any overfitting occurring in the model by misclassifying any class. For binary classification, it is a 2x2 table consisting of four entities which are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

Table 3.1: Confusion matrix

<table>
<tr><th colspan="2" rowspan="2">Class Labels</th><th colspan="2">Predicted</th></tr>
<tr><td>Garbage</td><td>Not Garbage</td></tr>
<tr><td rowspan="2">Actual</td><td>Garbage</td><td>True Positive</td><td>False Negative</td></tr>
<tr><td>Not Garbage</td><td>False Positive</td><td>True Negative</td></tr>
<tr><td colspan="4">Positive= Garbage; Negative= Not Garbage</td></tr>
</table>

3.4.3 Precision

Precision is a ratio between correctly predicted positive predictions to all the predicted positive instances by the model. A high precision, hence, represents the model having a low false positive rate which indicates the reliability and good performance of the model. The formula to calculate precision is:

$$Precision = \frac{\text{No. of True Positive Predicitions (TP)}}{\text{No. of all Positive Predictions (TP+FP)}} \tag{3.2}$$

3.4.4 Recall

Recall, which is also known as sensitivity or true positive rate, is a measure of accurate positive predictions made by the model out of all the positive instances. In this study, recall is the ratio between the Garbage predictions and actual Garbage instances in the data.

$$Recall = \frac{\text{No. of True Positive Predicitions (TP)}}{\text{No. of all Positive instances (TP+FN)}} \tag{3.3}$$

3.4.5 F1-Score

The F1 score is a performance metric for classification tasks that combines precision and recall into a single value. The calculation involves finding the harmonic mean of precision and recall, resulting in a score that ranges from 0 to 1. A score of 1 indicates the highest performance.

$$F1\text{- }Score = \frac{\text{2 x Precision x Recall}}{\text{Precision+Recall}} \tag{3.4}$$

3.5 Prototype Development

The creation of an app prototype for the image classification tool is an important step towards proving the model's practical use and potential effect. This prototype development phase attempts to provide a user-friendly interface demonstrating the model's functionality and capabilities in a real-world setting. The major purpose of this prototype is to offer a visual depiction of how the classification tool works, allowing users to engage with the model naturally and intuitively. The app prototype development is consistent with the project's larger objective of proving the potential of deep learning-based image classification in waste management and environmental monitoring applications.

4. RESULTS AND DISCUSSION

In this section, we will be discussing the results of deep learning-based image classification of different models discussed in section 3.3. The data was split into three sets which were utilized to train, validate and test the three models. Among all models, YOLOv8 classification model performed the best, achieving the highest accuracy of 99.5% at 50 epochs. The details of the data, and evaluation of the results of each model have been described in the following sub-sections.

4.1 Data split and visualization

The data was split into a train, test and validation set using Roboflow as Figure 4.1 represents the number of instances in each class in each set. The number of images for each class in each set were split in such a way to avoid any class imbalance (Table 4.4.1).

Table 4.4.1: Number of images in each data split

	Garbage	Not Garbage	Total Images
Train Set	1270	1303	2573
Validation Set	379	356	735
Test Set	191	176	367

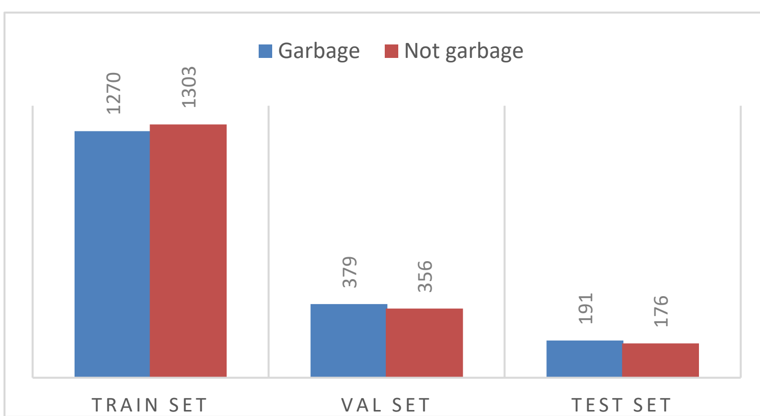


Figure 4.1: Bar chart describing splitting of data

The data can be visualized in Figure 4.2 as:

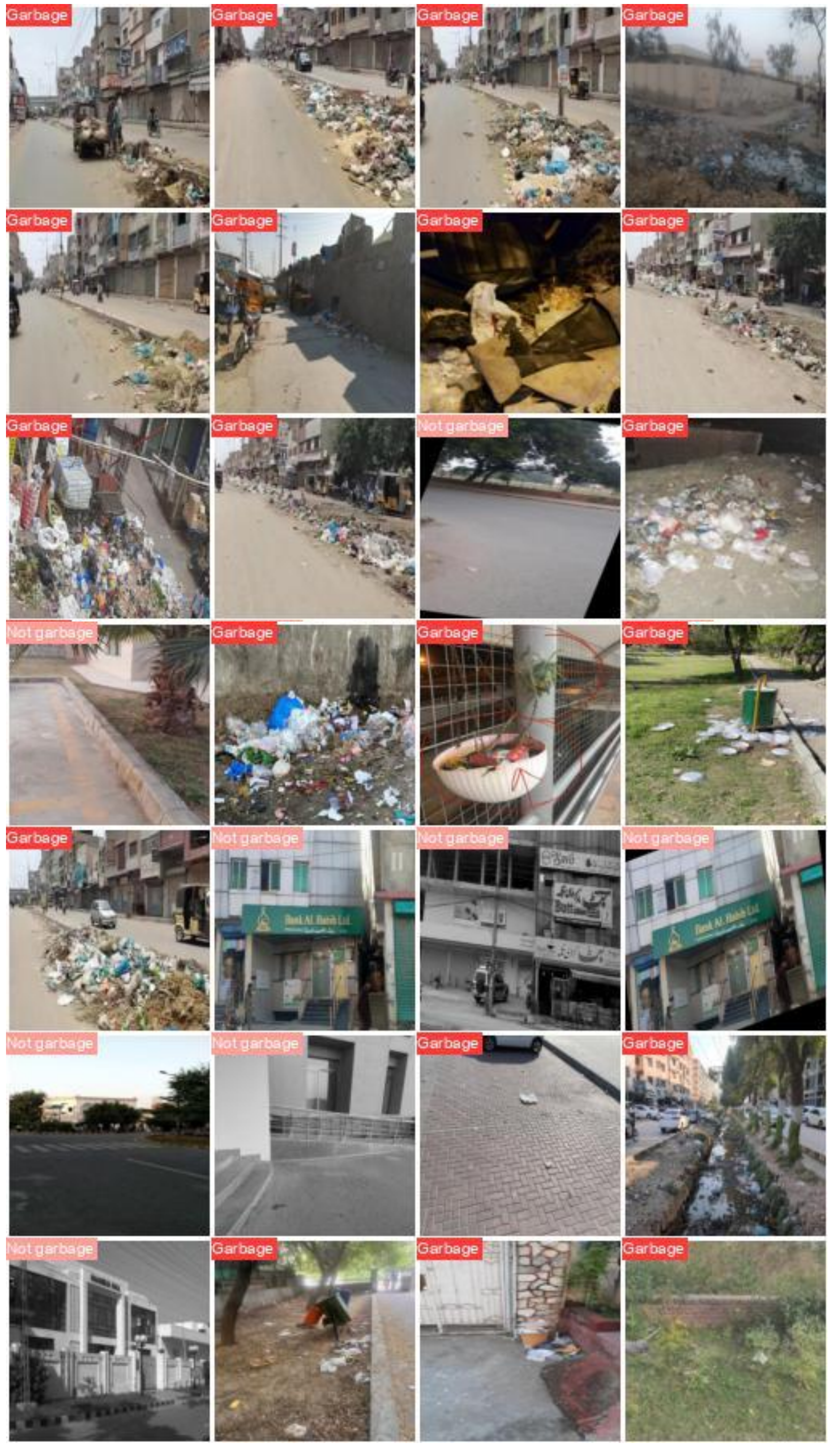


Figure 4.2: Few images visualized from the dataset

4.2 Inference of the pretrained YOLOv8 model

The YOLOv8 classification model was employed on our custom dataset and the model was trained via transfer learning. The weights of the model were adjusted and optimized to achieve maximum accuracy. Along this, the model was also trained at two different number of epochs (20 and 50). The model was trained at a batch size of 16 and an image size of 128x128 was set. A summary of the results obtained after training YOLOv8 model can be found in Table 4.2.

Table 4.2: Summary of results of training of YOLOv8 model

Epochs	Accuracy	Precision	Recall	F1-score
20	99.2%	0.98	1.00	0.98
50	99.5%	0.99	1.00	0.99

The accuracy and loss per epoch for training and validation at 50 epochs having highest accuracy is shown in Figure 4.3 and confusion matrix presented in Table 4.3.

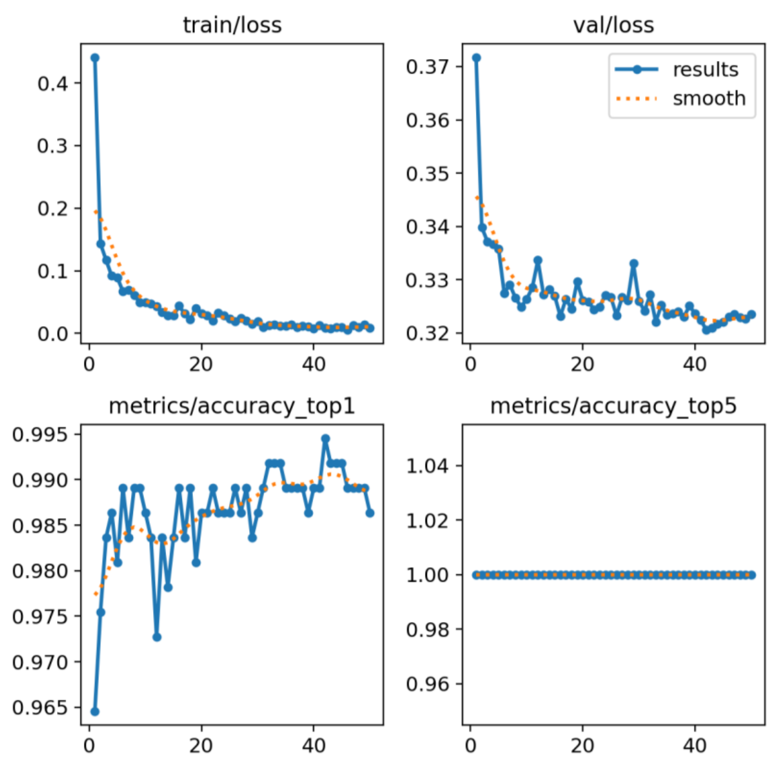


Figure 4.3: Accuracy and loss per epoch of YOLOv8 model at 50 epochs

Table 4.3: Confusion matrix for YOLOv8 model at 50 epochs

Predicted Labels		*True Labels*	
		Garbage	**Not Garbage**
	Garbage	189	0
	Not Garbage	2	176

4.3 Inference of the pretrained VGG19 model

The pretrained weights of VGG-19 classification model were applied to our custom waste dataset and the model was trained. The output layer of the model was adjusted to provide a binary classification result by applying sigmoid activation function. The model was trained on two different number of epochs (20 and 50), with an image size of 224x224 and a batch size of 16. A summary of the results obtained after training VGG-19 model can be found in Table 4.4.

Table 4.4: Summary of results of training of VGG-19 model

Epochs	Accuracy	Precision	Recall	F1-score
20	98.64%	0.98	0.99	0.99
50	98.91%	0.98	0.99	0.99

The accuracy and loss per epoch for training and validation at 50 epochs having highest accuracy is shown is shown in Figure 4.4 and confusion matrix presented in Table 4.5.

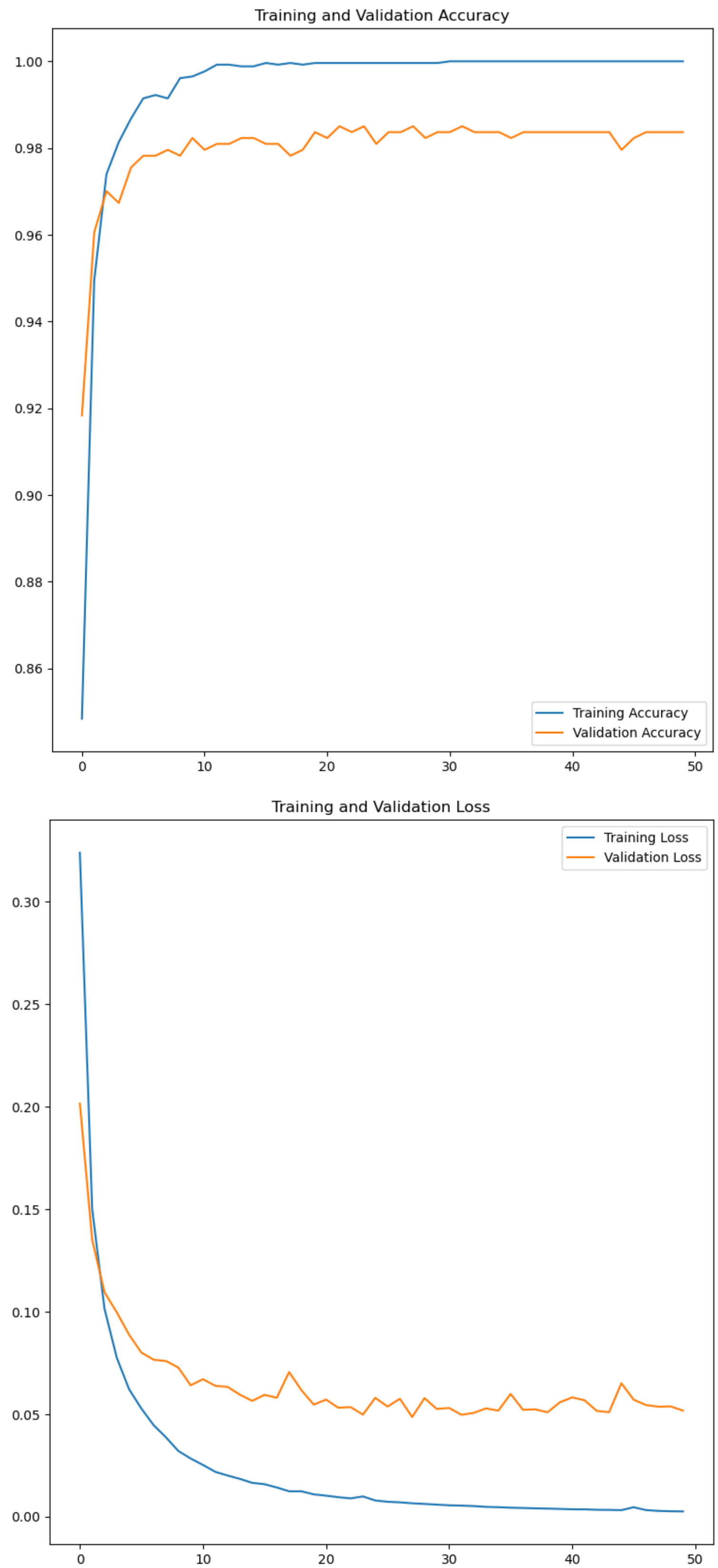


Figure 4.4: Training and validation accuracy (top) and loss (bottom) per epoch for VGG-19 at 50 epochs

Table 4.5: Confusion matrix for VGG-19 model at 50 epochs

Predicted Labels \ *True Labels*	Garbage	Not Garbage
Garbage	188	3
Not Garbage	1	175

4.4 Inference of the Deep CNN model

The deep CNN model built for the classification task was trained at three different learning rates of 0.001, 0.0001, and 0.00001 to obtain which learning rate would yield the best results. Moreover, for each learning rate the model was trained at 20 and 50 epochs.

4.4.1 At 20 epochs

For the model training at 20 epochs, the best accuracy was observed by a learning rate of 0.001, achieving an accuracy of 95.45%. Detailed results of other evaluation metrics for each learning rate are presented in Table 4.6.

Table 4.6: Summary of results of training of DCNN model at 20 epochs and different learning rates

Learning rate	Accuracy	Precision	Recall	F1-score
0.001	95.45%	0.97	0.94	0.95
0.0001	92.61%	0.98	0.87	0.92
0.00001	95.17%	1.00	0.90	0.95

The accuracy and loss per epoch for training and validation at 0.001 learning rate for highest accuracy is shown in Figure 4.5 and the confusion matrix is shown in Table 4.7.

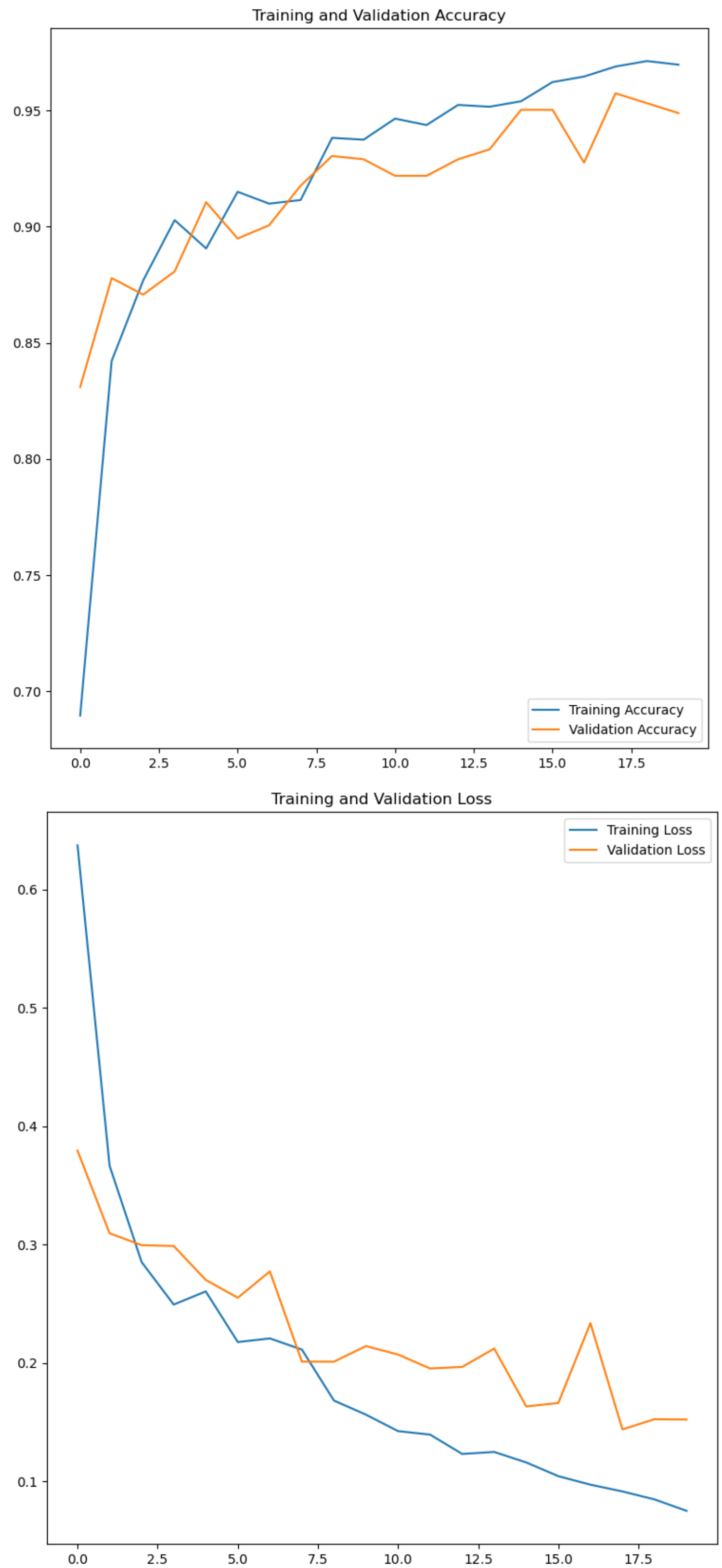


Figure 4.5: Training and validation accuracy (top) and loss (bottom) per epoch for DCNN at 20 epochs and 0.01 learning rate

Table 4.7: Confusion matrix for DCNN model at 20 epochs and 0.01 learning rate

Predicted Labels \ *True Labels*	Garbage	Not Garbage
Garbage	186	5
Not Garbage	11	165

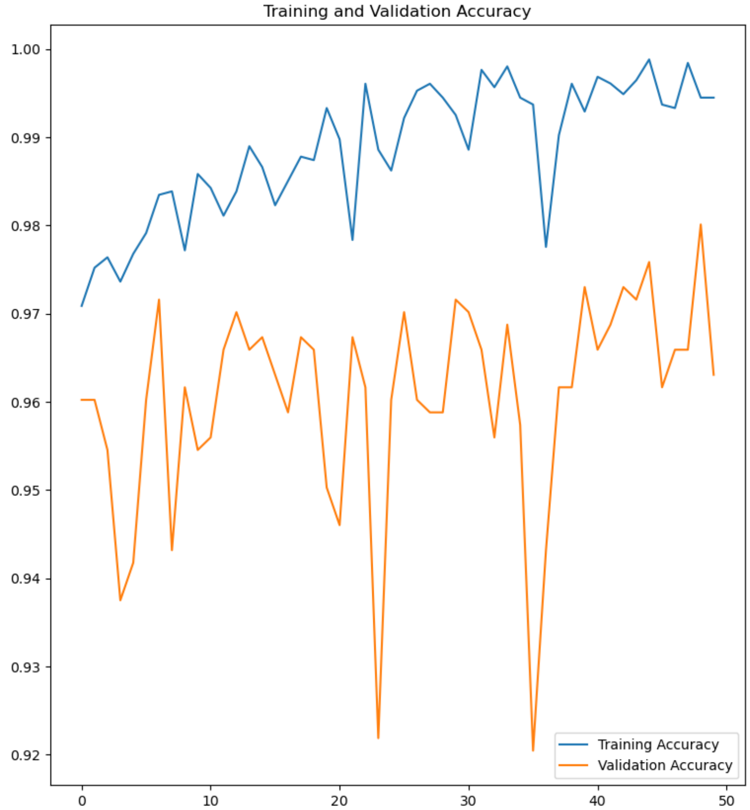
4.4.2 At 50 epochs

The deep CNN model trained at 50 epochs yields the maximum accuracy of 98.01% at a learning rate of 0.001, followed by an accuracy of 97.44% and 95.74% at learning rate of 0.00001 and 0.0001 respectively (as shown in Table 4.8).

Table 4.8: Summary of results of training of DCNN model at 50 epochs and different learning rates

Learning rate	Accuracy	Precision	Recall	F1-score
0.001	98.01%	0.98	0.98	0.98
0.0001	95.74%	0.96	0.95	0.96
0.00001	97.44%	0.99	0.95	0.97

The accuracy and loss per epoch for training and validation at 0.001 learning rate for highest accuracy is shown in Figure 4.6 and confusion matrix is presented in Table 4.9.



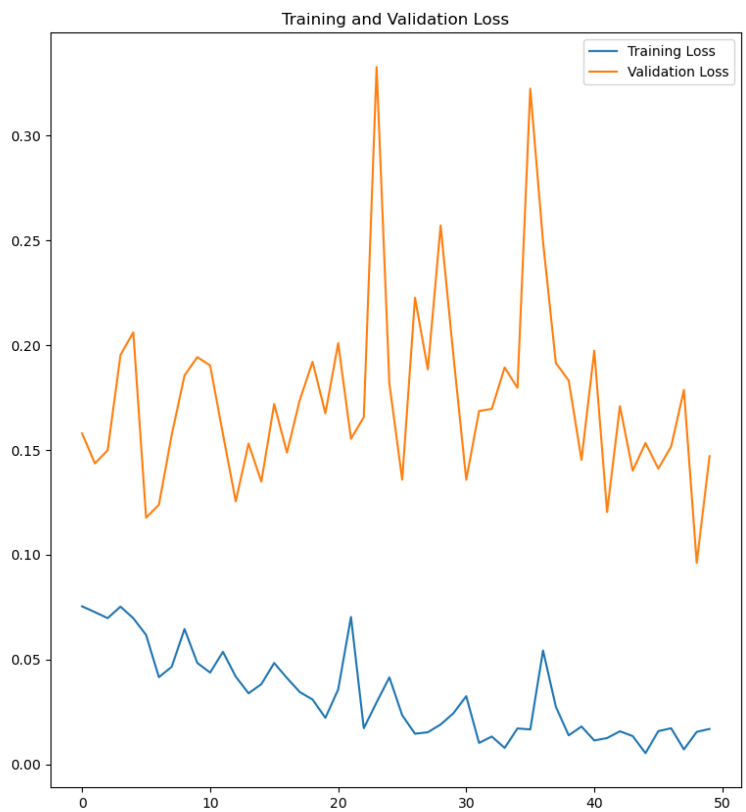


Figure 4.6: Training and validation accuracy (top) and loss (bottom) per epoch for DCNN at 50 epochs and 0.01 learning rate

Table 4.9: Confusion matrix for DCNN model at 50 epochs and 0.01 learning rate

Predicted Labels		*True Labels*	
		Garbage	**Not Garbage**
	Garbage	187	4
	Not Garbage	3	173

4.5 Prototype Development

Python includes multiple options to develop a graphical user interface (GUI) for different applications. One of the common ways to do so is by using Tkinter which standard Python interface to the Tcl/Tk GUI toolkit. A simple functional prototype for classification of waste images was developed utilizing Tkinter and the model with the highest accuracy was integrated in the prototype. Firstly, the Tkinter module was installed and imported, the saved model was provided, and the graphical components were defined to display predictions of every image. After running the code, the prototype application displayed as displayed in Figure 4.7.

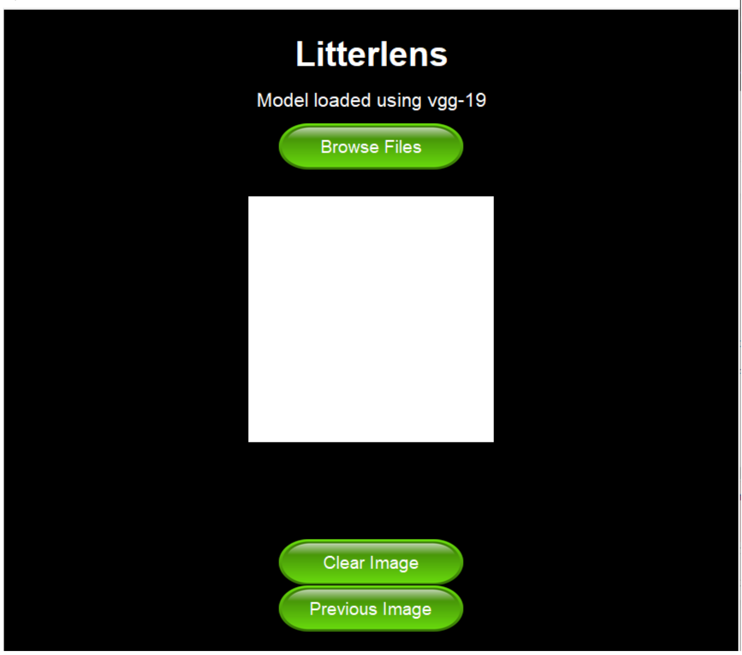


Figure 4.7: Prototype interface

After uploading an image, the predictions were displayed as seen in Figure 4.8 and Figure 4.9.

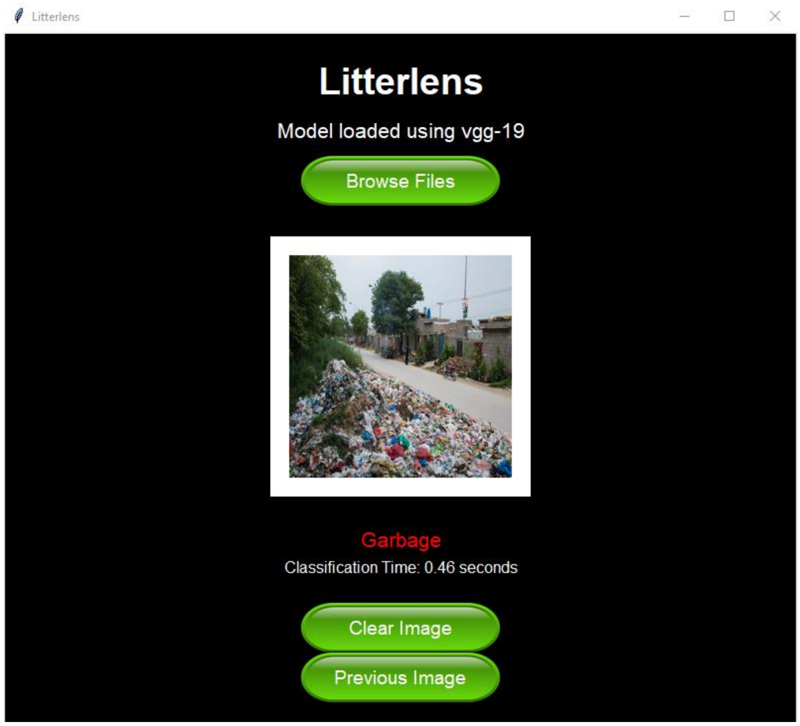


Figure 4.8: Prototype displaying prediction of Garbage

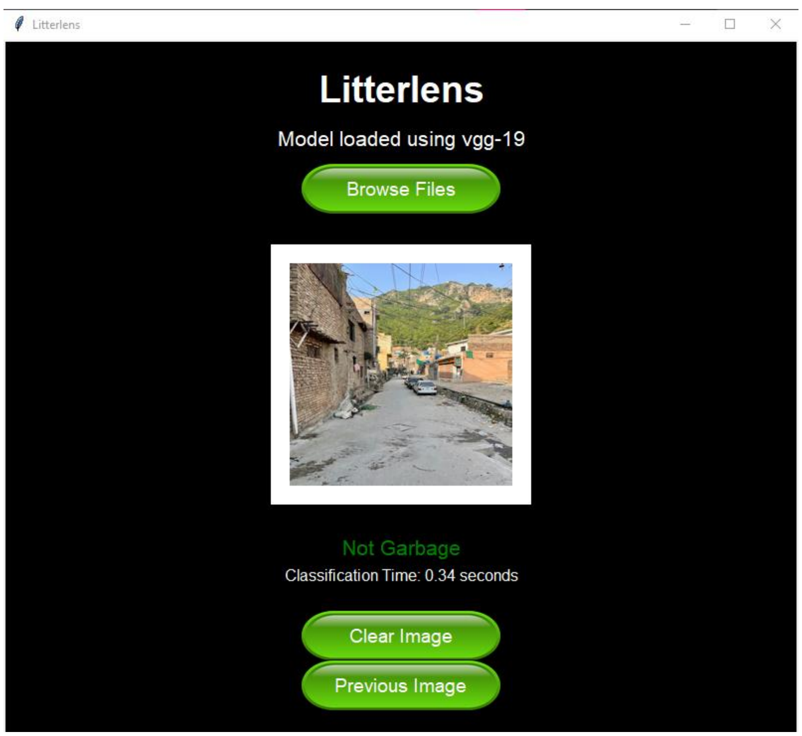


Figure 4.9: Prototype displaying prediction of Not garbage

Only two target classes, "Garbage" and "Not garbage," were selected for the purpose of this research. Many studies have explored the categorization of waste materials, with a particular emphasis on identifying specific classes based on their composition, such as plastic, glass, metal, and paper [42], [43]. Alternatively, some studies have focused on classifying waste based on its recyclability, distinguishing between organic, biodegradable, and non-biodegradable materials, among others [44], [45]. However, the classes we used in our research were selected for our specific scope. Our dataset was collected with the intention of being applicable to Pakistan as a whole, but in our community, waste is not properly segregated. Regardless of its composition, most waste is disposed of in plastic bags. Therefore, it can be challenging to differentiate waste based on its composition or recyclability. Examining waste data from multiple cities in Pakistan and applying different deep learning networks is a unique focus of this research. The three deep learning networks selected for this research were backed by a range of literature demonstrating their enhanced accuracy, efficiency, and speed in image classification tasks. YOLOv8 and VGG-19 both demonstrate exceptional performance and can be readily fine-tuned for specific datasets using transfer learning techniques. A deep CNN structure was chosen for its scalability, allowing for easy adjustment of layers and parameters to optimize results. Therefore, all three neural networks have demonstrated exceptional performance in binary image classification tasks studied in the literature. Among the three deep learning neural networks applied on our dataset, it was seen that YOLOv8 classification model was the best performing, achieving the highest accuracy of 99.5% at 50 epochs, followed by its performance at 20 epochs resulting in 99.2% accuracy. After that, VGG-19 classification model displayed a good accuracy of 98.91% at 50 epochs.

5. CONCLUSION

This research addressed the problem of the absence of an efficient and automated waste management system. The aims of our project included collection of a local waste dataset, utilizing the collected data for training and testing of deep learning models, and development of a tool by incorporating the best performing model. A local dataset of 3693 waste images was collected from Pakistani cities to train three deep learning models: Deep CNN, YOLOv8, and VGG-19. YOLOv8 emerged as the highest-performing model with an accuracy of 99.5% at 50 epochs. A functional prototype of the tool was created using Python Tkinter, integrating the best-performing model and providing classification results in under 1 second. This deep learning-based solution offers an efficient approach to waste management in Pakistan. In the future, it is recommended to utilize the dataset for other models such as object detection or segmentation to identify the composition and volume of the waste respectively. Moreover, the prototype can be developed into a fully functional web-tool or application.

5.1 Key Strengths

The major accomplishment of this research is the collection of a primary dataset of waste images in Pakistan as there existed no specialized dataset focusing on solid waste in Pakistan before. The dataset was used to train three deep learning models which all achieved the accuracy of more than 90% when trained at 20 and 50 epochs. This research also presented how the current waste management approaches can be improved by incorporating deep learning models which would not only help to automate the processes with efficiency, but also promote community engagement and achieve the goal of a smart city.

5.2 Limitations and Future recommendations

For future expansion of this project, it is recommended to modify the dataset in such a way that the composition of the waste materials can be detected by using object detection models. Moreover, it is also suggested to annotate the dataset into different classes based on the volume of waste so that the amount of garbage can be identified from the images by utilizing segmentation models. Hence, in accordance with the evolution of the project, the web-tool can also be developed from the existing prototype and incorporate other social features in the tool as well to make it more intuitive and friendly for the users.

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