Garbage Detection Using Deep Learning Methods (GD-DLM)

M. Mudasar Azeem[1]; Syed Anwaar Mehdi[2]; Muhammad Ali Shahid[3]; Mubasher Hussain[4]; Muhammad Adnan[5]; Spogmai[6]; Bilal Shabbir Qaisar[7*]

[1,4,5,6]Faculty of Computing University of Okara 56300, Pakistan
[2,3,7]Faculty of Comsats University Islamabad, Sahiwal Campus 57000, Pakistan

Corresponding Author: Bilal Shabbir Qaisar[7*]

Publication Date: 2025/09/16

Abstract: In today's expanding and densely populated world, it's crucial to design an automatic intelligent garbage sorter machine that uses advanced sensors. Garbage picture classification is a fundamental computer vision problem that must be solved before sensors can be included in this system. This research presents a model for autonomous trash classification using deep learning that can be applied in high-tech garbage sorting equipment. The 2,527 photos in the rubbish dataset are categorized into six types: trash, cardboard, glass, metal, paper, and plastic. The next step is the creation of GD-DLM, a deep learning model for garbage categorization that is an upgrade from Xception and DenseNet121 models. At last, the tests are run to evaluate GD-DLM against the best-of-breed approaches to garbage classification. The suggested Xception and DenseNet-121 models scored 92.11% and 88.63%, respectively, compared to the baseline accuracy.

Keywords: *Machine Learning; Resnet50v2; Trauma; Medical Images.*

How to Cite: M. Mudasar Azeem; Syed Anwaar Mehdi; Muhammad Ali Shahid; Mubasher Hussain; Muhammad Adnan; Spogmai; Bilal Shabbir Qaisar (2025) Garbage Detection Using Deep Learning Methods (GD-DLM). *International Journal of Innovative Science and Research Technology,* 10 (9), 608-618.
https://doi.org/10.38124/ijisrt/25sep396

I. INTRODUCTION

The natural and anthropogenic sources of waste that end up on urban roadway surfaces include things like leaves, dirt, silt, litter, and illicit dumping. Ineffective street cleaning has the potential to damage the city's economy, reputation, and tourism. It has also been acknowledged that unclean roadways may significantly contribute to water and air pollution [14, 20]. Studies have demonstrated that individuals are more prone to litter when they see litter on the streets. People are more likely to think twice before throwing anything and ultimately refrain from littering if the streets are clean. Keeping city streets clean is essential since it affects not just the city's reputation and image but also the quality of life for city dwellers and employees.

Numerous municipalities have implemented a variety of strategies and exerted a substantial amount of work in order to enhance the cleanliness of their streets. As an illustration, New York public utilised a program known as Scorecard for the purpose of evaluating the cleanliness of its public streets and sidewalks. A stringent photographic standard of cleanliness for streets and pavements serves as the basis for the measures. An index of cleanliness was presented by Sevilla in 2013 for the city of Granada, which is located in southern Spain, in order to quantify the level of cleanliness on the streets. In 2015, Imteaj developed an application for the city of Dhaka, which is the capital of Bangladesh, that was built on the Android operating system. It is possible for the user to make a contribution to the cleanliness of his city by either contacting the city corporation or signalling to volunteers to come forward. As of the year 2015, the city of Los Angeles had established a cutting-edge method for evaluating the cleanliness of each individual street. A map depicting the cleanliness of each and every one of Los Angeles' blocks was created for the first time by the city. With the help of this new tool, Sanitation is better able to target locations that have a high demand for services and to ensure that services are distributed consistently. The majority of the technologies that are now in use for identifying trash are not entirely automated and still rely on human intervention. This is despite the fact that these methods provide fresh ideas for communities to clean their streets. Therefore, in order to assess whether or not the roadway is dirty, the cleanup crews will need to manually collect and identify each photo. For this reason, a system that is both promising and ideal should be able to detect trash in each collected image in an autonomous and reliable manner without the need for human interaction.

Convolutional neural network (CNN) methods [1] are currently the norm for state-of-the-art object identification

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

and recognition systems; these systems rely on deep architectures like VGG. Such solutions work, but they are computationally expensive in processor, memory, and storage space requirements. Hence, in many applications with computational limits, like mobile devices, their utilisation is not practical. The usage of "mobile" CNN architectures—lightweight CNN designs tailored for mobile devices—is one viable alternative that has been investigated in the literature. But as far as we are aware, no research has yet looked at how to evaluate appropriate litter detectors with neural network topologies, especially in cases when devices have limited processing power. Also, there are a lot of cloud computing services for machine learning, but they don't have fast enough reaction times for real-time applications. This is particularly true in outdoor areas like forests and beaches, where network connection is spotty at best. In addition, there is an increase in power consumption during data transfer via the network. Thus, adopting lightweight neural networks has several benefits, such as reduced energy usage, local processing, and efficiency.

Mynation has lately implemented policies to reduce its own waste output in light of the concerning global increase in trash creation over the past few years. A domestic waste management system for controlled release, recycling, transportation, and treatment of waste is now mandated by the most recent round of revisions to the "Law on Preventing and Controlling Environmental Pollution by Fixed Wastes" of the People's Republic of China, which took place in 2020. Currently, the majority of the public environment's trash sorting occurs in a limited number of designated areas. Ineffective sorting is just one of several issues; another is the unpleasant working environment. It may be as simple as sorting trash at home to get to the core of the issue. Landfills collect an overwhelming variety of waste products, and it's hard to keep track of them all since individuals lack a basic understanding of classification and hence seldom separate waste into discrete groups. A lot of people have been thinking about getting home care robots recently. One example is the rapid industrialisation and widespread public adoption of sweeping robots, which were among the first products of their kind. Concurrent with this, mass production of automobiles began. A lot of the sweeping robots on the market now aren't very smart, even though they have some basic features like path planning, autonomous charging, and obstacle avoidance.

Our top goal should be maintaining a clean, healthy environment for future generations. Several issues with employing deep learning for garbage detection have been raised in the current research. One problem was that several categories, including but not limited to cardboard, cardboard, glass, metal, paper, plastic, and trash, had yet to be included in earlier research. This research aims to address these gaps in the existing literature.

The current study proposes a Deep Learning Method for Garbage Detection (GD DLM), which would identify the dataset. The proposed method would be trained on the garbage dataset, which contains six classes such as cardboard, glass, metal, paper, plastic, and trash. A deep learning technique would be suggested for the improvement of accuracy. Following the main contributions of this research:

- Developed a Garbage Detection System using Deep Learning Methods (GD-DLM) that recognizes the cardboard, glass, metal, paper, plastic, and trash classes.
- Improved the accuracy of the existing deep learning model.

II. LITERATURE REVIEW

A number of outstanding individuals have made indelible marks in the field of waste management-related machine learning and internet of things (IoT). An image processing and Convolutional Neural Network (CNN) garbage categorisation system was built in a later study [11] (Bobulski and Kubanek, 2019). Their research has been focused solely on detecting polyethylene. A battery of tests was run by the researchers to determine the presence of terephthalate, polyethylene, polypropylene, and polystyrene. Capsule-Net, a neural network that can differentiate between plastic and non-plastic products, was employed by the scientists for solid waste management (Sreelakshmi et al., 2019). Two publicly available datasets were determined to have an accuracy of 96.3% and 95.7%, respectively, by the writers. The full integration was built and tested using multiple pieces of hardware.

In a recent work (Huiyu and O, O. G. Kim, S. H., 2019), the author developed a novel garbage categorisation model by utilising deep learning processes. This method was also used for recycling waste. Adedeji and Wang (2019) put out the idea that a deep learning model may be used to automatically identify trash. The authors also mentioned that the model was employed for the purpose of sorting recyclable waste. The authors of the article state that in order to classify trash, they utilised a Support Vector Machine and a pre-trained Convolutional Neural Network (CNN) called ResNet-50 (Nowakowski and Pamua, 2020). Comparing the model to a publically available dataset revealed an accuracy rate of 87%. A recent study looked into a new method of identifying and categorising e-waste, or electronic trash (Misra et al., 2018). Classification was carried out using the CNN model, while the identification of different types of e-waste was accomplished using the RCNN model. The researchers discovered an accuracy range of 90% to 97% for both detection and classification. Using the IoT for trash management was not mentioned in any of the articles [11, 21, 23, 19, 24].

An essential approach to automated, resilient waste management was presented in a publication [26]. The authors demonstrated a smart garbage can using the ultrasonic sensor in conjunction with a number of gas sensors. Additionally, they suggested using a cloud server and an Android app to provide a live feed of trash. Here, ML methods were completely disregarded. A clever and economical waste management system was concocted by the author of a paper [4, 41]. As a result of the Internet of Things, the authors have

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

integrated a number of devices, including a GSM module, an ultrasonic sensor, and an Arduino small. When the trash level rose above a certain point, the GSM module would notify the user by text message. Each user received an audio message after the system was upgraded with a PIR motion sensor and a memory card. Author also claimed sufficient performance from the proposed system. In this study, the authors [19] created a method for intelligent waste management in urban areas. We came up with a model that was efficient and cost-effective. You may get some information about it in the article [6].

The authors have created a model that optimises garbage collection using the Internet of Things. An infrared sensor and a Raspberry pi form its basis. Better results from the garbage collection procedure may be achieved if the system management rescheduled and redirected the waste. According to a report [9], someone built an intelligent trash can that could measure the amount of trash. All of the proposed models made use of wireless networking and a web server. The scientists determined the amount of trash still in the bin using an infrared distance measuring device. A website transmitted these findings and data bits to an Android app. Using IoT and a Raspberry Pi, the authors of a paper [18] built an intelligent trash can. The paper's authors found that by using an IoT-based smart garbage system, they were able to decrease food waste. The designers integrated all the parts into a unified whole using mesh technology. A server and router were the components of the suggested model for collecting and analysing data on food poisoning. There was a 33% reduction in food waste as a result of the numerous successful trials that were carried out. While there were a number of articles that discussed trash management [31, 22, 37], no one had actually laid out a plan for the system using terms from the deep learning paradigm. The study's authors apparently succeeded in developing a mobile trash pickup robot, as seen in [25]. Using deep learning techniques, the authors claimed their suggested architecture could correctly identify trash.

By using a subset of ImageNet in 2012, Krizhevsky et al. trained one of the biggest CNNs for the ILSVRC-2012 and ILSVRC-2010 competitions [12]. This was the foundation for the study of Girshick et al. [16]. In what methods is the detection performance of the Pascal Voc Dataset evaluated? When RPNs are paired with CNNs, the resulting approach is called R-CNN. It took a lot of time and effort to train a regional CNN. It was suggested that SPPnets [17] be used to accelerate R-CNN. In 2015, Girshick [15] created Faster R-CNN, a training method that fixes errors produced by R-CNN and SPPnet, making them faster and more accurate. In 2016, Ren et al. [29] suggested a Faster Regional CNN to decrease computing time. Keep in mind that the convolutional layers used by the Regional Proposal Network detector and the Faster Regional CNN detector are identical. From what we have learnt about Convolutional Neural Networks (CNNs), we deduced that a faster Regional CNN model would be ideal for street rubbish identification.

III. METHODOLOGY

➢ *Materials and Methods*

Self-teaching algorithms are crucial to the development of AI. Algorithms of this type can change and improve as more data is collected about a project [35]. The result of solutions-oriented technology is ongoing. For self-learning software to function, it must have access to these conceptualizations [7]. In the same way that genuine neural networks are structured into layers, artificial neural networks (ANNs) similarly connect their nodes (neurons). This neural network stores information, processes algorithms (with the weighting of either plus or minus), and provides sensory feedback. The layered architecture and attention to detail of ANNs show promising results. These networks are capable of "deep learning" [27, 28].

In this research, we build a deep transfer learning system for waste classification. After the problem of class imbalance in the dataset has been fixed, various augmentation methods are utilised to generate a large quantity of additional data. In the second stage, attributes are automatically extracted, and pre-trained algorithms for recognising and classifying rubbish are used. Figure 1 is a flowchart depiction of the suggested procedure.

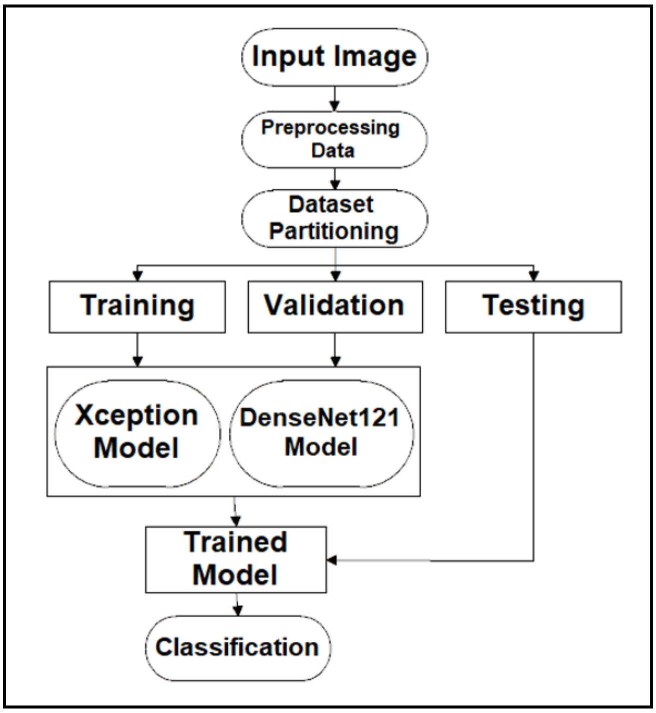

Fig 1 Flow Chart of the Presented Method.

➢ *Garbage Dataset*

The largest and highest-quality collection of garbage-related viral images available for research is found in the garbage dataset archive [2]. As a whole, the six types of garbage included in the collection constitute 2527 images. Figure 2 depicts the range of possible class configurations. The photographs were arbitrarily assigned to their correct categories.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

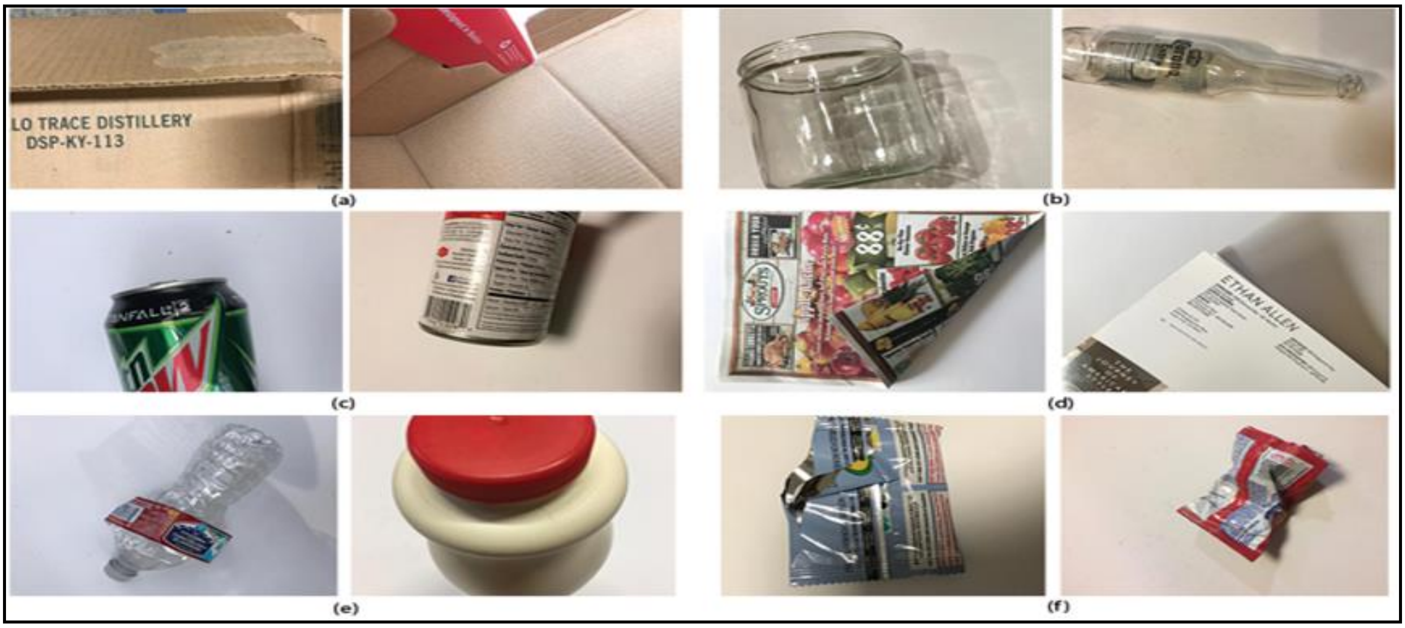

Fig 2 (a) Cardboard, (b) Glass, (c) Metal, (d) Paper, (e) Plastic, and (f) Trash are Classes of the Garbage Dataset.

➢ *Image Pre-Processing*

To guarantee more consistent classification results and better features, each image in the garbage dataset is preprocessed. Since there is a chance of overfitting while training using the CNN approach, having a sizable image dataset was essential.

➢ *Image Resizing*

There are 6000 × 4000 variations of each image in the trash dataset. The size of the dataset has been modified to be 224 × 224. The model's performance will be severely reduced in exchange for halving the processing time.

➢ *Training, Validation, and Testing*

The garbage dataset produced training, validation, and testing sets. All photo labels were correctly predicted using the proposed Garbage Detection using Deep Learning Method (GD-DLM) on a labelled dataset. The GD-DLM model was trained on the training dataset, and its efficacy was assessed on the validation and test datasets. Therefore, we separated our data sets into three equal parts: 60% for training, 20% for validation, and 20% for testing. Table 1 shows that 2527 images were used for training, validation, and testing on the rubbish dataset. In this work, the model was trained using data divided into six categories, representing 60% of all photos. The remaining 40% of images were used for testing and validation with the rubbish dataset.

Table 1 Summary of the Garbage Dataset

Split	Classes	Label Samples	Total Samples
Training	cardboard	287	1768
	glass	354	
	metal	286	
	paper	403	
	plastic	347	
	trash	91	
Validation	cardboard	46	328
	glass	65	
	metal	56	
	paper	83	
	plastic	61	
	trash	17	
Testing	cardboard	70	431
	glass	82	
	metal	68	
	paper	108	
	plastic	74	
	trash	29	
Total			2527

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

➢ *Architecture of DenseNet121 Base Model*

The forward pass of a typical Convolutional Neural Network is quite simple, as seen in Figure 3 below, and it results in a predicted label for the input image. Aside from the first convolutional layer, which processes the input image directly, subsequent convolutional layers process the output of the preceding layer to generate a feature map. L-direct connections exist, connecting the previous and next layers in an L-layered structure.

Adensely Connected Convolutional Network (DenseNet) describes a network architec ture in which every layer communicates with every other layer. L(L+1)/2 direct connections between adjacent L-th layers. Each layer feeds into the next using the feature maps from the layers below it, and each layer above it uses the feature maps from the layers above it.

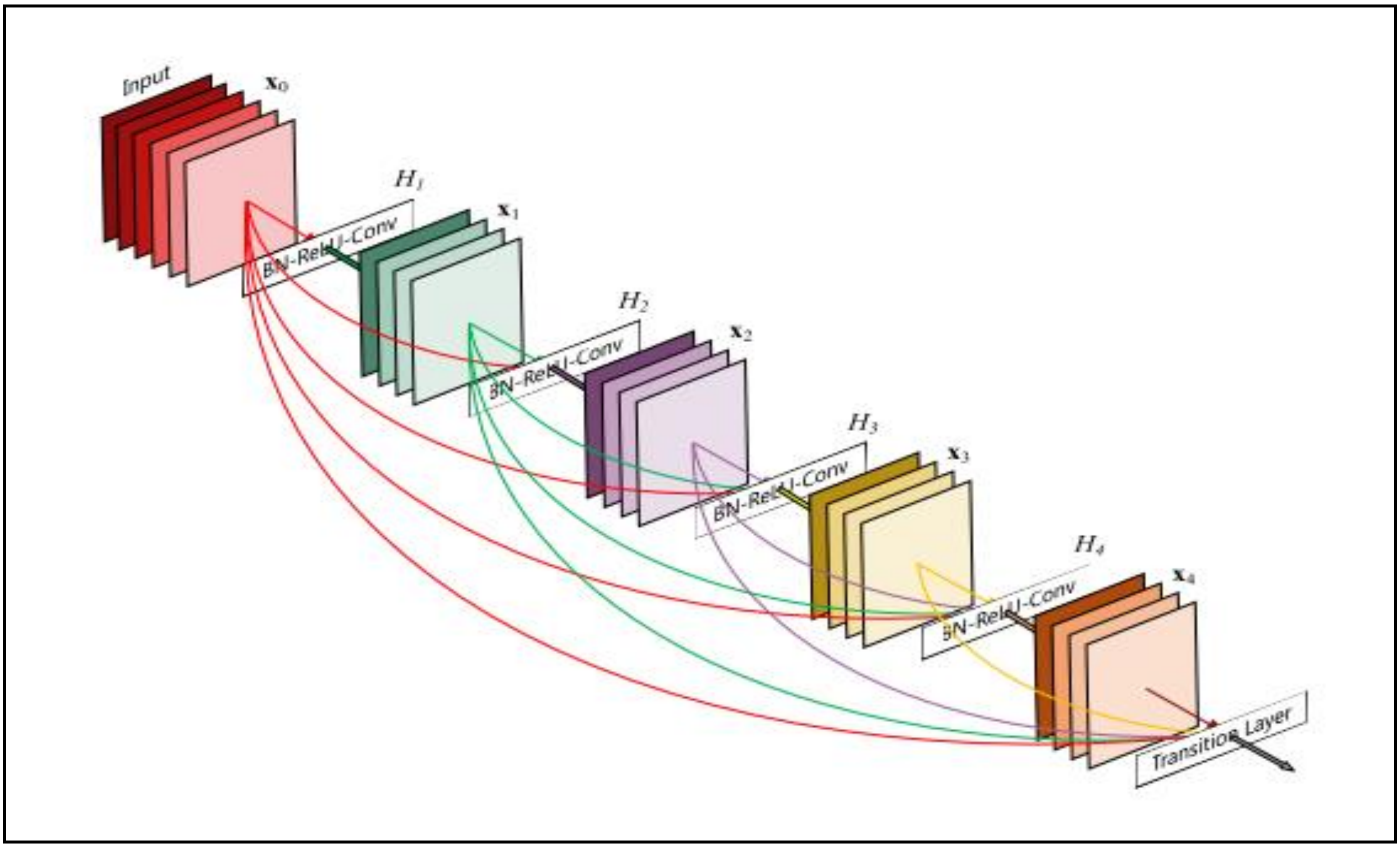

Fig 3 Architecture of the DenseNet121 Model.

➢ *Architecture of Xception Base Model*

Scientists have developed inception modules that bridge the depth-separable convolution method and the regular convolution utilised in convolutional neural networks (a depthwise convolution followed by a pointwise convolution). One way to conceptualise a depth separable convolution in this context is as an Inception module with a maximum height restriction. Using these findings, we provide a novel architecture for a deep convolutional neural network that eliminates the need for Inception modules in favour of depthwise separable convolutions. On a dataset including 350 million pictures and 17,000 classes, our Xception [13] approach surpasses Inception V3. However, Xception [13] outperforms Inception V3 somewhat on the ImageNet dataset (for which Inception V3 was built). The Xception design has improved performance through increased capacity and more efficient use of model parameters.

The Xception neural network design uses depth-separable convolutions to complete complex tasks. The engineers at Google came up with the idea. For convolutional neural networks, Google recommends using inception modules as a "middle ground" between regular convolution and the depth-wise separable convolution approach (a depthwise convolution followed by a pointwise convolution). With this analogy in mind, it’s easy to see how a depthwise separable convolution is analogous to an infinitely tall Inception module. They propose a unique Inception-like architecture for deep convolutional neural networks that use depthwise separable convolutions in place of Inception modules to take advantage of this discovery.

Compared to traditional convolutions, depth-separable variants are expected to reduce calculation time significantly. In Figure 4, we see the analysed data.

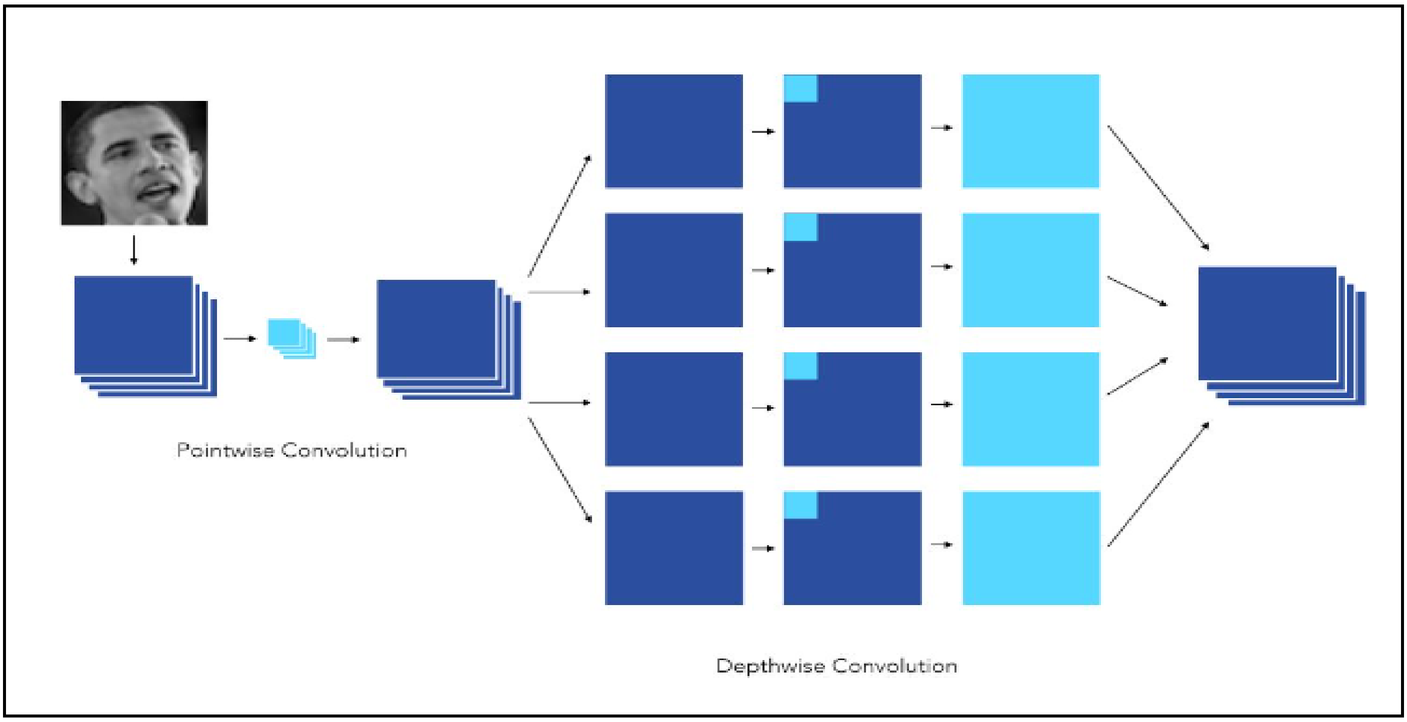

Fig 4 Depthwise Separable Convolution

➢ *Evaluation Measures*

The testing dataset was used to evaluate the suggested approach following the training phase. We tested the architecture's efficacy using recall, accuracy, F1 score, and precision. We will examine the performance metrics utilized in this research in the parts that follow. What follows is a mathematical definition and representation of the terms "true positive," "true negative," "false negative," and "false positive."

- *Classification Accuracy*

The accuracy of a classification system can be evaluated by determining what percentage of its predictions were correct and what percentage were incorrect.

Accuracy = T P+T N / (T P+T N +FP+FN)

- *Precision*

When analysing the effectiveness of a model, classification accuracy may not always be the most appropriate metric to employ. For instance, this is one of the scenarios where there is a considerable gap in socioeconomic status. It's a safe bet to assume that each sample is of the highest possible quality. If the model isn't picking up any new information, it would be irrational to infer that all components belong to the best class. Therefore, when we talk about accuracy, we refer to the fluctuation in findings you receive while measuring the same object several times with the same tools. The term "precision" refers to one of these statistics and can be defined as follows:

Precision = T P / (T P+FP)

- *Recall*

Another critical parameter is called recall, and it refers to the percentage of input samples that are of a type that the model can accurately predict. The formula for the recall is as follows:

Recall = T P / (T P+FN)

- *F1 Score*

The F1 score is a statistic utilised to contrast recall and precision.

F1 Score = 2 * (Precision * Recall) (Precision + Recall)

IV. RESULTS AND DISCUSSION

As part of our training and evaluation, we used high-powered Graphics Processing Units (GPUs) on a brand-new Google Colab [3] Pro account. To accomplish this, we utilized transfer deep learning models. Training of the proposed GD-DLM with Sparse Categorical Crossentropy loss functions was carried out in all trials with the Adam optimizer and a learning rate of 0.0001. During the training phase, which included 10 iterations and an initial batch size of 8, the best Val_loss models were retained. The Xception and DenseNet121 models recommended the following parameters: 8 batches, 5 epochs, early termination, and model saving based on Val_loss.

➢ After augmenting it using various methods, we used the garbage dataset to evaluate the performance of the provided Xception and DenseNet121 models.
➢ When compared to its predecessors, the suggested GD-DLM demonstrates significant improvement in terms of accuracy.

Volume 10, Issue 9, September – 2025 International Journal of Innovative Science and Research Technology
ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

➢ *The Performance Analysis of the Proposed Garbage Detection using Deep Learning Methods (GD-DLM)*

- *The Performance of Xception Base Model*

The performance of the Xception baseline model was measured using the garbage data set. From the end of the first epoch to the end of the most recent epoch, the accuracy of the model validation grew from 86.01% to 92.99%. As can be seen in Figure 5, the training accuracy improves from 72.34% after the first epoch to a final value of 98.53%. As can be seen in Figure 5, Xception's validation loss was drastically cut down from an initial value of 40.69% to just 26.16%. After the first training session, the loss was 85.18%, and it was 6.39% after concluding training, which is identical to the initial loss.

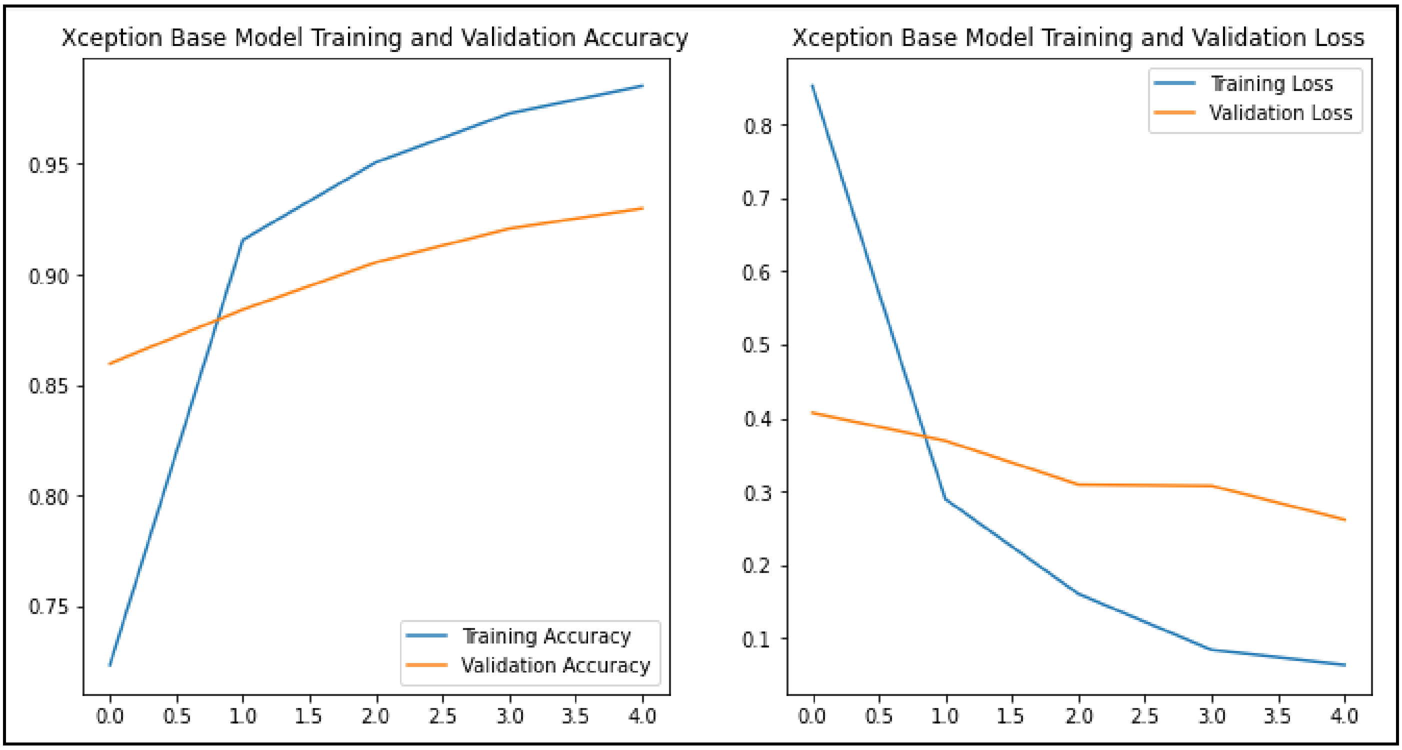

Fig 5 The Xception Base Model of Accuracy and Loss Graph

Table 2 shows the results of an unobserved test set on the Xception base model. The model's overall accuracy on the test set was 92.11%; however, Xception performed exceptionally well on the cardboard class, with a precision of 98%, a recall of 93%, and an F1-score of 96%. The average values for the F1 score, precision, and recall for the glass class were 93%, 92%, and 94%, respectively. The metal class had an average F1 score, recall, and precision of 91%, 90%, and 91%, respectively. The paper's class performs exceptionally well, with a 95% F1 score, 95% recall, and 95% precision. A typical F1 score, precision, and recall for the plastics category were 89%, 86%, and 92%. For the rubbish class, the average values for F1 score, precision, and recall were 83%, 92%, and 76%, respectively.

Table 2 Precision, Recall, F1 Score, and Accuracy of the Xception Base Model

Performance Measures	Precision	Recall	F1 Score	Accuracy
cardboard	98%	93%	96%	92.85%
Glass	92%	94%	93%	93.90%
Metal	90%	91%	91%	91.18%
Paper	94%	95%	95%	95.37%
Plastic	86%	92%	89%	91.89%
Trash	92%	76%	83%	75.86%
Average Accuracy				92.11%

A confusion matrix was used to assess the classification accuracy of different models visually. Rows in the confusion matrix that are not on the diagonal represent predictions that turned out to be erroneous. Each class's associated Xception base model demonstrated that deeper hues suggested more important classification accuracy, but lighter shades told misclassified data. The confusion matrix from the test set will be used to evaluate Xception's performance (shown in Figure 6). The confusion matrix shows that when the default parameters for the Xception model are employed, 92.11% of the data are correctly identified, leaving only 7.89% unaccounted for. According to the confusion matrix, the Xception base model successfully classified all six samples.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

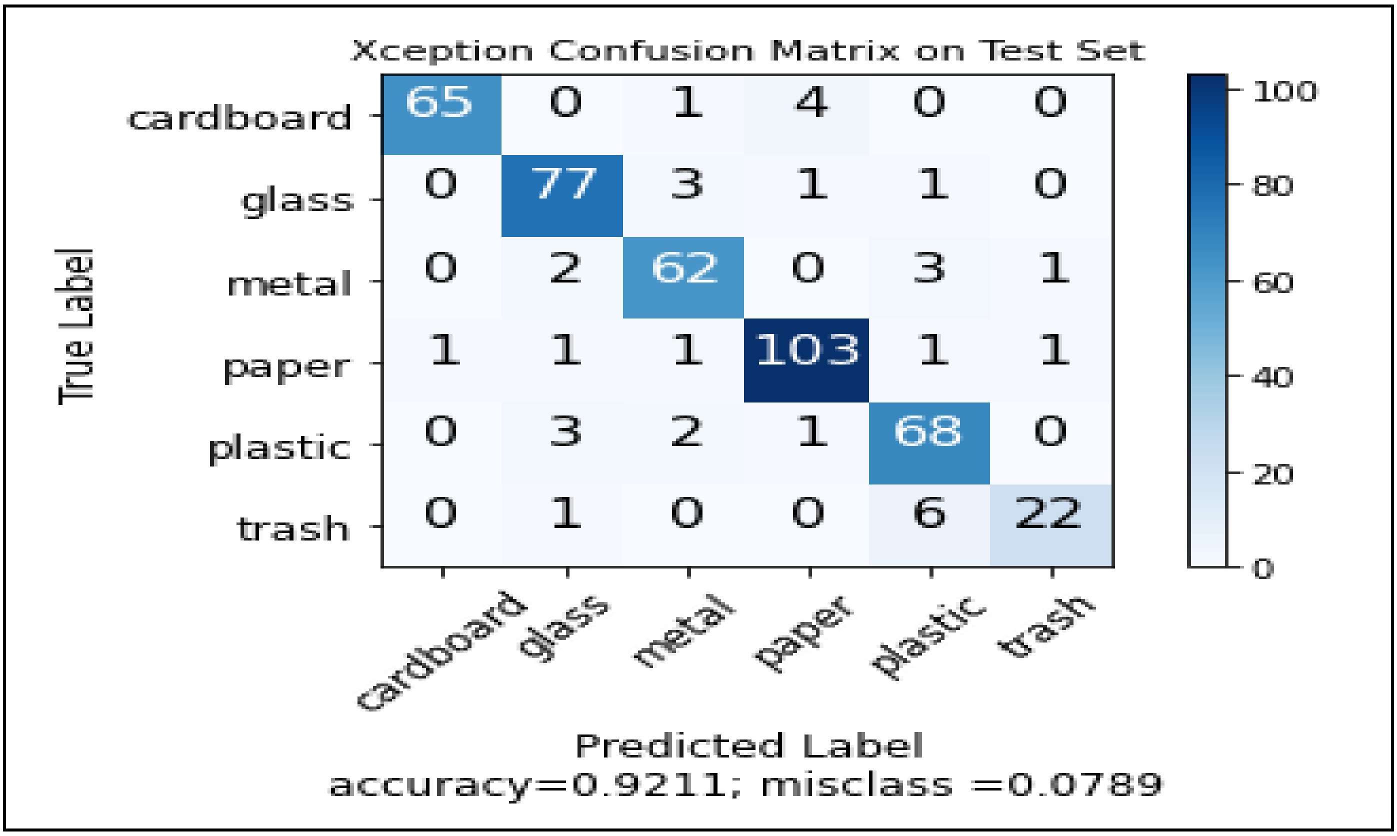

Fig 6 The Xception Base Model Confusion Matrix on Test Set.

- *The Performance of DenseNet121Base Model*

The performance of the DenseNet121 model was analysed on the garbage dataset. After the first epoch, the model's validation accuracy was 82.32%; after the most recent epoch, it was 88.11%. Figure 6 depicts the training accuracy improving from 72.68% after the first epoch to 97.34% after the last epoch. Figure 7 displays a significant reduction in validation loss for DenseNet121, from 54.67% to 40.84%. As an added note, the training loss was 75.03% after the first period and 10.11% after the final training, both consistent with the initial loss.

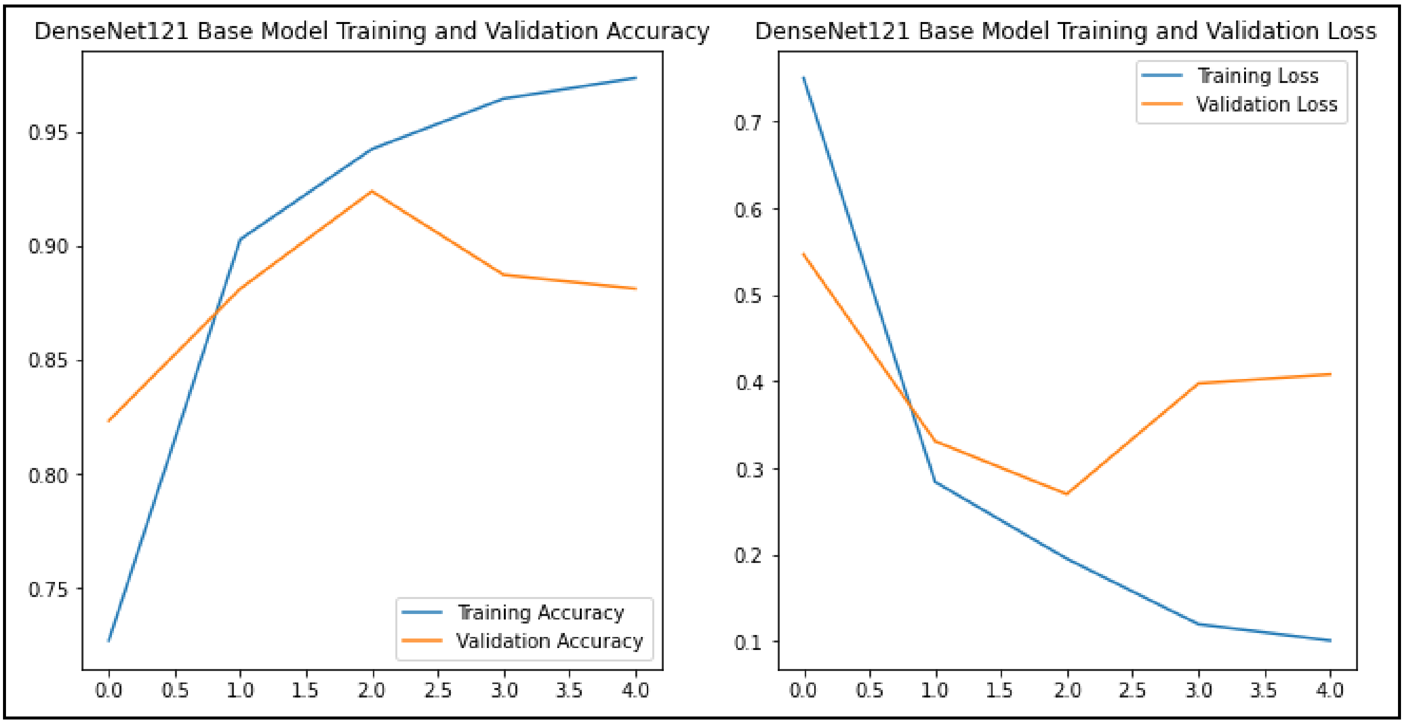

Fig 7 The DenseNet121 Base Model of Accuracy and Loss Graph.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/25sep396

Table 3 shows how the DenseNet121 baseline model fared on an unknown test set. While the model's overall accuracy was 86.63% across all classes in the test set, DenseNet121 performed best on the cardboard class, with a precision of 79%, a recall of 96%, and an F1-score of 86%. The average F1 score, precision, and recall for the glass class were 90%, 90%, and 84%. The average F1 score, precision, and recall for the metal class were 89%, 94%, and 91%. The paper class is outstanding, with a 97% F1 score, a 79% recall rate, and a 97% precision rate. On average, the F1 score, precision, and recall for the plastics category were 89%, 84%, and 89%. The recall was 87%, the accuracy was 88%, and the F1 score was 88% on average for the rubbish class.

Table 3 Precision, Recall, F1 Score, and Accuracy of the DenseNet121 Base Model

Performance Measures	**Precision**	**Recall**	**F1 Score**	**Accuracy**
cardboard	79%	96%	86%	97.71%
Glass	97%	84%	90%	86.25%
Metal	89%	94%	91%	94.12%
Paper	97%	79%	87%	78.70%
Plastic	84%	96%	89%	95.95%
Trash	87%	90%	88%	89.66%
Average Accuracy				88.63%

We could visually compare the models' ability to classify data using a confusion matrix. Diagonal rows in the confusion matrix represent incorrect predictions. The more accurate classification was achieved by the corresponding DenseNet121 base model for each class, as indicated by darker colors, while lighter colors depicted less precise classification. To evaluate DenseNet121, we will employ confusion matrices from the test set (shown in Figure 8). As shown in the confusion matrix, the DenseNet121 baseline model's predictions are consistent across all image types. The confusion matrix demonstrates that when the DenseNet121 model was trained with the default settings, 88.63% of the data were categorised correctly, and 11.37% were misclassified. By comparing confusion matrices across all 6 samples, we can see that the DenseNet121 baseline model achieves excellent results.

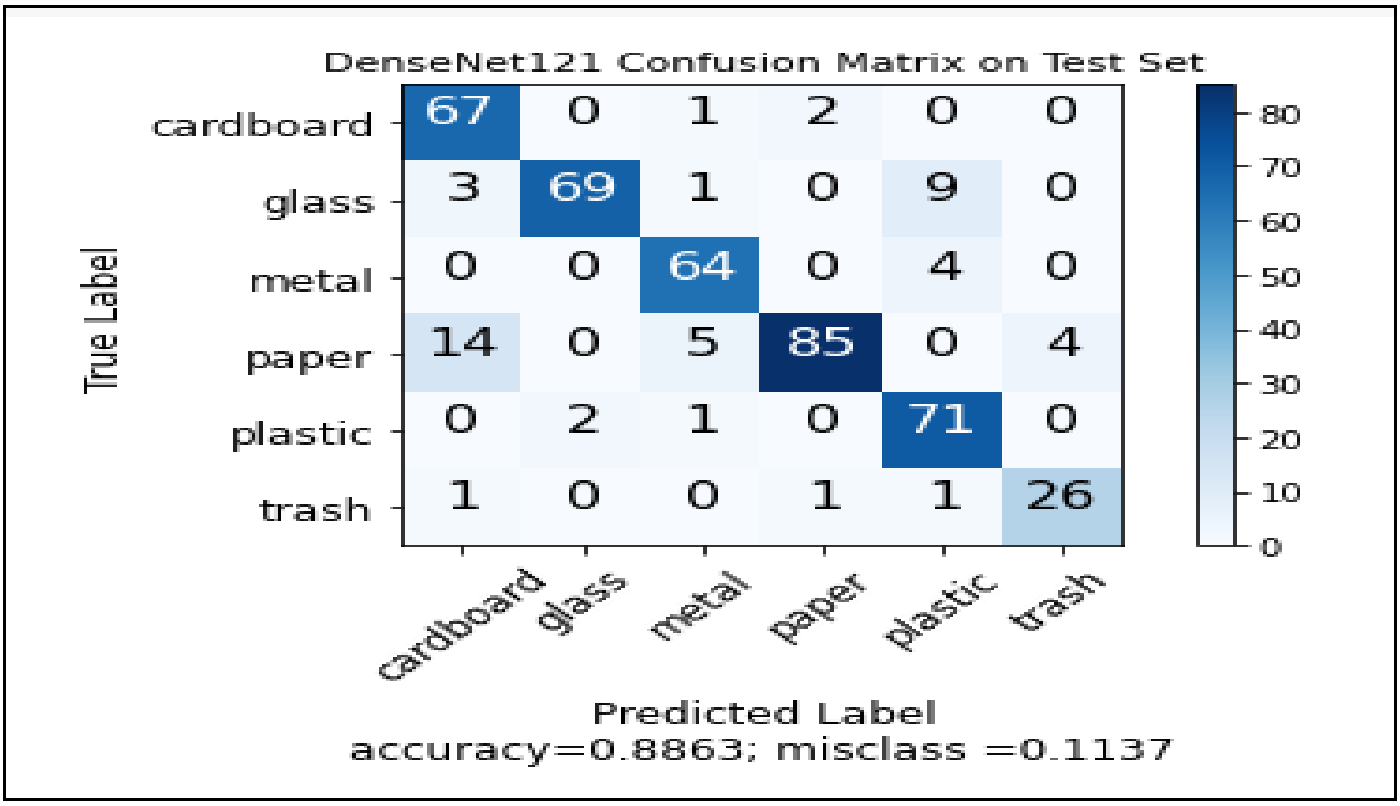

Fig 8 The DenseNet121 Base Model Confusion Matrix on Test Set.

Table 4 Classification Accuracy of Proposed Model on Test Set.

Description	**Model Name**	**Accuracy**
GD-DLM	Xception Base Model	92.11%
GD-DLM	DenseNet121BaseModel	88.63%

V. CONCLUSION

The research described in this manuscript explored using Convolutional Neural Networks to recognize trauma in real-time using machine learning techniques. For trauma detection, this method is both reliable and quick. The test findings demonstrate a remarkable accuracy rate in identifying people who are either trauma disease or normal. The trained model completed the task using the ResNet50V2 model, achieving an individual accuracy of 99.40%.

The best way to train a CNN model to identify and recognize trauma diseases in humans is to integrate multiple models and evaluate their performance accuracy. In addition, the authors recommend an improved optimizer, more precise parameter values, enhanced tuning, and models for adaptive transfer learning.

ACKNOWLEDGMENT

Special thanks go to Comsats University Islamabad, Sahiwal Campus, for providing the IT services, Lab, and server provisions that enabled the smooth writing of the manuscript.

REFERENCES

[1]. Rashid, J., Qaisar, B. S., Faheem, M., Akram, A., Amin, R. U., & Hamid, M. (2024). Mouth and oral disease classification using InceptionResNetV2 method. Multimedia Tools and Applications, 83(11), 33903-33921.
[2]. Shifrin, A., et al., Posttraumatic stress disorder treatment preference: Prolonged exposure therapy, cognitive processing therapy, or medication therapy? Psychological Services, 2022.
[3]. Tyagi, A.K. and P. Chahal, Artificial intelligence and machine learning algorithms, in Challenges and applications for implementing machine learning in computer vision. 2020, IGI Global. p. 188-219.
[4]. Ghosh, P., et al., Efficient prediction of cardiovascular disease using machine learning algorithms with relief and LASSO feature selection techniques. IEEE Access, 2021. 9: p. 19304-19326.
[5]. Ramos-Lima, L.F., et al., The use of machine learning techniques in trauma-related disorders: a systematic review. Journal of Psychiatric Research, 2020. 121: p. 159-172.
[6]. Bharde, P., R.V. Sai, and S. Sripriya, Role of computed tomography imaging in the diagnosis of blunt and penetrating abdominal trauma injuries. International Journal, 2023. 10(1): p. 10.
[7]. Sharma, A.K., et al., Medical image classification techniques and analysis using deep learning networks: a review. Health informatics: a computational perspective in healthcare, 2021: p. 233-258.
[8]. Chen, Y.-H. and M. Sawan, Trends and challenges of wearable multimodal technologies for stroke risk prediction. Sensors, 2021. 21(2): p. 460.
[9]. Le Glaz, A., et al., Machine learning and natural language processing in mental health: systematic review. Journal of medical Internet research, 2021. 23(5): p. e15708.
[10]. Yeo, M., et al., Review of deep learning algorithms for the automatic detection of intracranial hemorrhages on computed tomography head imaging. Journal of neurointerventional surgery, 2021. 13(4): p. 369-378.
[11]. Hussain, S., et al., Modern diagnostic imaging technique applications and risk factors in the medical field: a review. BioMed research international, 2022. 2022(1): p. 5164970.
[12]. Brunner, M., et al., Social media and people with traumatic brain injury: a metasynthesis of research informing a framework for rehabilitation clinical practice, policy, and training. American journal of speech-language pathology, 2021. 30(1): p. 19-33.
[13]. Buhrmester, V., D. Münch, and M. Arens, Analysis of explainers of black box deep neural networks for computer vision: A survey. Machine Learning and Knowledge Extraction, 2021. 3(4): p. 966-989.
[14]. Ponnusamy, V., et al., AI-Driven Information and Communication Technologies, Services, and Applications for Next-Generation Healthcare System. Smart Systems for Industrial Applications, 2022: p. 1-32.
[15]. Gipson, J., et al., Diagnostic accuracy of a commercially available deep-learning algorithm in supine chest radiographs following trauma. The British Journal of Radiology, 2022. 95(1134): p. 20210979.
[16]. Choi, J., et al., The impact of trauma systems on patient outcomes. Current problems in surgery, 2021. 58(1): p. 100849.
[17]. Cheng, C.-T., et al., A scalable physician-level deep learning algorithm detects universal trauma on pelvic radiographs. Nature communications, 2021. 12(1): p. 1066.
[18]. Sundkvist, J., et al., Epidemiology, classification, treatment, and mortality of adult femoral neck and basicervical fractures: an observational study of 40,049 fractures from the Swedish Fracture Register. Journal of orthopaedic surgery and research, 2021. 16: p. 1-10.
[19]. Puttagunta, M. and S. Ravi, Medical image analysis based on deep learning approach. Multimedia tools and applications, 2021. 80(16): p. 24365-24398.
[20]. Tulbure, A.-A., A.-A. Tulbure, and E.-H. Dulf, A review on modern defect detection models using DCNNs–Deep convolutional neural networks. Journal of Advanced Research, 2022. 35: p. 33-48.
[21]. Gudigar, A., et al., Automated detection and screening of traumatic brain injury (TBI) using computed tomography images: a comprehensive review and future perspectives. International journal of environmental research and public health, 2021. 18(12): p. 6499.
[22]. Pitt, J., Y. Pitt, and J. Lockwich, Clinical and cellular aspects of traumatic brain injury, in Handbook of Toxicology of Chemical Warfare Agents. 2020, Elsevier. p. 745-765.

[23]. Qaisar, B. S. (2025). Canker and Cold Sore Classification Using Xeception Technique. Journal of Machine Learning and Deep Learning (JMLDL), 2(01).
[24]. Inam Ul Haq; Ahmad Ali; Bilal Shabbir Qaisar; Hafiz Muhammad Adnan; Mubasher Hussain; Muhammad Nauman.“Steganography Techniques for Medical Images: A Recommender Paper.” " Volume. 8 Issue. 9, September - 2023 International Journal of Innovative Science and Research Technology (IJISRT), www.ijisrt.com. ISSN - 2456-2165, PP :- 79-87. https://doi.org/10.5281/zenodo.8340603.
[25]. Hamid, S., et al., Dual-energy CT: a paradigm shift in acute traumatic abdomen. Canadian Association of Radiologists Journal, 2020. 71(3): p. 371-387.
[26]. Bilal Shabbir Qaisar; Mahammad Ali Shahid; Sunil Ashraf; Muhammad Adnan; M. Mudasar Azeem; Maham Ali; Muhammad Nauman. “Automated Trauma Detection by Using Machine Learning.” Volume. 10 Issue.8, August-2025 International Journal of Innovative Science and Research Technology (IJISRT), 2129-2135 https://doi.org/10.38124/ijisrt/25aug1009.
[27]. Shabbir Qaisar, B., Mudasar Azeem, M., Nauman, M., & Yasin, J. (2024). Monkeypox virus detection using deep learning methods. International Journal of Computing and Digital Systems, 16(1), 189-198.
[28]. Mudasar Azeem, M., Ul Haq, I., Nauman, M., Talha Hashmi, M., & Shabbir Qaisar, B. (2024). MASK DETECTION USING DEEP LEARNING METHODS. International Journal of Computing and Digital Systems, 15(1), 1-9.