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# Machine Learning And Deep Learning In Waste Sorting

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**ABSTRACT:** Recycling is already a significant work for all countries. Among the work needed for recycling, garbage classification is the most fundamental step to enable cost efficient recycling. Segregation of garbage is also a primary concern in many nations across the world. Even though we are in the modern era, many people still do not know how to distinguish between organic and recyclable waste. It is because of this that the world is facing a major crisis of waste disposal. Population growth and the acceleration of urbanization have led to a sharp increase in municipal solid waste production, and researchers have sought to use advanced technology to solve this problem. Machine learning (ML) algorithms are good at modelling complex nonlinear processes and have been gradually adopted to promote solid waste management and help of the sustainable development of the environment in the past few years. In this paper, we attempt to classify the garbage waste object in images and classify it into seven categories that are cardboard, paper, glass, metal, plastic (mainly domestic waste), e-waste and medical waste. The proposed approaches are simulated and evaluated based on image processing and machine learning. The models we used include multi-kernel support vector machines (SVM) and random forest (RF). The model works in 80-20% training and testing pattern that provides the 86.01% of accuracy for the testing.

***Keywords— garbage classification, image processing, machine learning, support vector machine.***

## 1.INTRODUCTION:

The increasing urbanization of India poses so many threats as with increase in population land consumption increases, utilities increase, consumption of food increases, use of resources increases and more than these the quantity of waste generated by 1.37 billion people increases. Waste management system is a large challenge for urban areas among most parts of countries all over the world. A huge quality of garbage is increased each and every day in India. It is sad to know that 5% of this huge amount of garbage is recycled. The only solution to this problem is to identify and classify the garbage at the initial stage by itself. The proper separation process of waste is managed so as to get less number of risks on our health and ecosystem. Presently there is no best and profitable system for classification of wastes. Our point is to reduce the physical efforts and effectively segregate the waste and for this we have modified hybrid classifier model [1]. “The Hybrid Classifier” model is the combination of Deep Learning (DL) and Supervised Machine Learning (ML). The constant growth of deep learning models contributes the remarkable improvements in the field of computer vision. Convolutional neural network (CNN) is one of the deep learning models widely used in image classification, detection and segmentation. Deep learning is a subset of machine learning that uses artificial neural networks to process and analyse information. Neural networks are composed of computational nodes that are layered within deep learning algorithms. Each layer contains an input layer, an output layer, and a hidden layer. The neural network is fed training data which helps the algorithm learn and improve accuracy. When a neural network is composed of three or more layers it is said to be "deep", thus called deep learning. Supervised machine learning model that uses labelled training data (structured data) to map a specific input to an output. In supervised learning, the output is known (such as recognizing a picture of paper) and the model is trained on data of the known output. In simple terms, to train the algorithm to recognize pictures of paper, feed it pictures labelled as paper [2]. The significance of waste classification, monitoring and disposal has increased due to the increase in industrial development and the process of intelligent urbanization. Manual sorting is less effective which is primarily used in developing nations. However, handling manual sorting leads to health issues and it is costly and requires more manpower. As a result, using deep learning to the classification of trash benefits both the environment and the workers' health. The purpose of this model is to recognize the type of waste and categorize into seven categories that are cardboard, metal, paper, plastic, glass, e-waste and medical. By implementing this garbage classification, we want to reduce the physical efforts and effectively segregate the waste into different categories. Our model gives more accuracy that is about 86.01% which is more than the existing model [3]. This model works in mainly four phases that:

**1.1 Collection of Dataset:** The dataset we have taken for our model is from Kaggle, which is standard benchmark site. The dataset is classified into different types such as glass, paper, metal, cardboard, plastic, medical and e-waste. It is important to train the model to get best accuracy. Initially, it is labelled and sequential of images have taken place. Further it is divided into two categories: training and testing dataset.

**1.2 Pre-processing of images:** Various functions on images at cheapest rate of abstraction whose goal is to improve the images dataset that conquer undesired deformation or increase some image information important for next processing is known as Image pre-processing. Pre-processing plays an essential role to get the best results. Under this, we can perform various operations such as image-size, labels, batch-size, rescale.

**1.3 Training Data:** In machine learning, a common goal is to study and develop algorithms that learn from previous achievements and make various predictions on a dataset. In our model we have used InceptionV3 convolutional neural network model which is used as a feature extractor. For training our model we have consider total 160 images of each category.

InceptionV3 is the feature extractor that used in model works by using a deep learning architecture that consists of multiple parallel convolutional layers with varying kernel sizes and depths. These layers are designed to capture different features in the input images, such as edges, textures, and shapes. The model then combines the outputs of these layers to make predictions about the input image's class or category. InceptionV3 also employs techniques like batch normalization and dropout to improve its training efficiency and generalization capabilities.

**1.4 Testing Data:** Test data is the data that is used in the test of a software system. Specifically identified data is known as test data. Test data can be generated by automation tools, and we can also generate test data by testers. Mainly in regression testing data test is used as the same data that can be used again and again.

Random Forest algorithm is a powerful tree learning technique in Machine Learning. It works by creating a number of decision training during the training phase. Each tree is constructed using a random subset of the data set to measure a random subset of features in each partition. This randomness introduces variability among individual trees, reducing the risk of overfitting and improving overall prediction performance [4].

Our objective is to bring about an automated process to the existing laborious method where the process is faster, cleaner and does not affect the ecosystem. The biodegradable products must be put to decompose and the rest, recycled. Resources must be saved, and they must not be extinguished. In other words, "To minimize human intervention and increase machine utilization". With the help of Machine Learning technology, we aim towards creating an efficient waste-management system that segregates waste into seven different categories like cardboard, glass, paper, metal, plastic, e-waste, medical and allows further easier collection along with effective recycling of waste [5].

## 2. LITERATURE REVIEW:

S. Meng et.al. [1] attempt to identify single garbage object in images and classify it into one of the recycling categories. They study several approaches and provide comprehensive evaluation. The models we used include support vector machines (SVM) with HOG features, simple convolutional neural network (CNN), and CNN with residual blocks. According to the evaluation results, we conclude that simple CNN networks with or without residual blocks show promising performances. Thanks to deep learning techniques, the garbage classification problem for the target database can be effectively solved.

L. R. Kambam et.al. [2] presents an approach to identify the type of plastics depending upon its material, it can be concluded whether the plastic can be recycled or not. In this approach, visual and physical properties were used to classify the plastic materials. It makes use of the fact that recycled plastics are having some similar features like weight, pressure and colour. Given an image of a plastic object, these features will form a dataset to train different classifiers which will classify the given plastic into recycled or non-recycled. A colour-based segmentation algorithm is used to detect colour and KNN classifier is used to predict the colour of plastic. A tactile touch sensor is used to calculate the pressure that can be applied on the plastic object. Different types of plastics are having inconsistent set of features. Therefore, perceptively we are using four different classifiers for the classification namely SVM, KNN, Decision tree and Logistic Regression.

J. Shah et.al. [3] proposes to use deep learning algorithms to help solve this problem of waste classification. The waste is classified into two categories like organic and recyclable. Their proposed model achieves an accuracy of 94.9%. Although the other two models also show promising results, the Proposed Model stands out with the greatest accuracy. With the help of deep learning, one of the greatest obstacles to efficient waste management can finally be removed.

Yang D. et.al.[4] proposed Fast.AI ResNet framework was designed to find out the best architecture, pre-processing, and training parameters for the models largely automatically. The accuracy and F1-score were both above 96% in the diagnosis of COVID19 using CT-scan images. In addition, we applied transfer learning techniques to overcome the insufficient data and to improve the training time. The binary and multi-class classification of X-ray images tasks were performed by utilizing enhanced VGG16 deep transfer learning architecture. High accuracy of 99% was achieved by enhanced VGG16 in the detection of X-ray images from COVID-19 and pneumonia. The accuracy and validity of the algorithms were assessed on X-ray and CT-scan well-known public datasets. The proposed methods have better results for COVID-19 diagnosis than other related in literature. In our opinion, our work can help virologists and radiologists to make a better and faster diagnosis in the struggle against the outbreak of COVID-19.

W. Xia et.al. [5] proposes population growth and the acceleration of urbanization have led to a sharp increase in municipal solid waste production, and researchers have sought to use advanced technology to solve this problem. Machine learning (ML) algorithms are good at modelling complex nonlinear processes and have been gradually adopted to promote municipal solid waste management (MSWM) and help the sustainable development of the environment in the past few years. In this study, more than 200 publications published over the last two decades (2000–2020) were reviewed and analysed. This paper summarizes the application of ML algorithms in the whole process of MSWM, from waste generation to collection and transportation, to final disposal. Through this comprehensive review, the gaps and future directions of ML application in MSWM are discussed, providing theoretical and practical guidance for follow up related research.

Zhou H. et.al.[6] propose a deep learning-based classification method, in which ResNeXt is a suitable deep neural network for practical implementation, followed by transfer learning methods to improve classification results. We pay special attention to the problem of medical waste classification, which needs to be solved urgently in the current environmental protection context. We applied the technique to 3480 images and succeeded in correctly identifying 8 kinds of medical waste with an accuracy of 97.2%; the average F1-score of five-fold cross-validation was 97.2%. This study provided a deep learning-based method for automatic detection and classification of 8 kinds of medical waste with high accuracy and average precision. We believe that the power of artificial intelligence could be harnessed in products that would facilitate medical waste classification and could become widely available throughout China.

Olugboja Adedeji et.al.[7] proposes an intelligent waste material classification system, which is developed by using the 50-layer residual net pre-train (ResNet-50) Convolutional Neural Network model which is a machine learning tool and serves as the extractor, and Support Vector Machine (SVM) which is used to classify the waste into different groups/types such as glass, metal, paper, and plastic etc. The proposed system is tested on the trash image dataset, which was developed by Gary Thung and Mindy Yang, and is able to achieve an accuracy of 87% on the dataset. The separation process of the waste will be faster and intelligent using the proposed waste material classification system without or reducing human involvement.

Cuiping Shi et.al. [8] imposes a waste classification method based on a multilayer hybrid convolution neural network (MLH-CNN). The network structure of this method is similar to VggNet but simpler, with fewer parameters and a higher classification accuracy. By changing the number of network modules and channels, the performance of the proposed model is improved. Finally, this paper finds the appropriate parameters for waste image classification and chooses the optimal model as the final model. The experimental results show that, compared with some recent works, the proposed method has a simpler network structure and higher waste classification accuracy. A large number of experiments in a TrashNet dataset show that the proposed method achieves a classification accuracy of up to 92.6%, which is 4.18% and 4.6% higher than that of some state-of-the-art methods and proves the effectiveness of the proposed method.

Li. Cao et.al.[9] proposes a method of garbage classification and recognition based on transfer learning, which migrates the existing InceptionV3 model recognition task on the Imagenet dataset to garbage identification. First, increase the data set through data augmentation. Then build a convolutional neural network based on the source model and adjust the neural network parameters based on the training effect. The training results show that the training accuracy is 99.3% and the test accuracy is 93.2%. Finally, the model is applied to the pictures collected in real life for recognition. The recognition results show that the model has good performance and high accuracy, can correctly identify common garbage in life, and has reference significance for intelligent garbage classification, which proves the feasibility of this method.

Ishika Mittal et.al [10] proposes to build a real time application which recognizes the type of waste and categorize it into defined categories. By implementing this Trashnet classification system, we want to reduce the physical efforts and effectively segregate the waste into different categories. The model used for this study is Convolution Neural Network (CNN), a Machine Learning algorithm which is used on a dataset containing images of garbage. This system ensures a best way for waste management and will also speed up the segregation process with higher accuracy. This study lasts with remarkable results and is successful to classify various images of waste in correct classes.

Kishan PS et.al. [11] focused on detecting and classification garbage using Deep Learning and Neural Network algorithms. CNN algorithm is used, applied, and analysed. Confusion matrix and ROC curve are also used. Here in this paper, two different datasets are used, one dataset was available online, and another dataset was built on our own. This paper comparison both datasets by using different algorithms like CNN, SVM, faster-RCNN, and values are recorded for future use.

Aghilan M. et.al. [12] proposes machine learning is an area with a huge potential for the transformation of many areas of life and science including industrial informatics. The investigated methods include the existing manually engineered model and its modification as well as conventional machines learning algorithms. This paper presents the use of automated machine learning for solving a practical problem of a real-life Smart Waste Management system.

Cheema SM et.al.[13] proposes a waste grid segmentation mechanism, which maps the pile at the waste yard into grid-like segments. A camera captures the waste yard image and sends it to an edge node to create a waste grid. The grid cell image segments act as a test image for trained deep learning, which can make a particular waste item prediction. The deep-learning algorithm used for this specific project is Visual Geometry Group with 16 layers (VGG16). The model is trained on a cloud server deployed at the edge node to minimize overall latency. By adopting hybrid and decentralized computing models, we can reduce the delay factor and efficiently use computational resources. The overall accuracy of the trained algorithm is over 90%, which is quite effective. Therefore, our proposed (SWMACM-CA) system provides more accurate results than existing state-of-the-art solutions, which is the core objective of this work.

S. Varudandi et.al.[14] proposed in this research will lend a hand to solve these waste management problems. The main constituent of this system is a waste bin which will automatically segregate the waste by employing technologies such as Internet of Things and Machine Learning. The bin is connected to the cloud to assist in systematic waste collection by tracking and uploading various data points for a particular bin. A group of these bins will help in efficient garbage collection and management starting from the origin of the waste itself. An Android application which is also a part of this system will assist the relevant authorities to manage the bins as per real time requirements. Two versions of the system are elaborated in this paper with the first version achieving an accuracy of 75% in classifying the waste as wet or dry whereas the second version achieves an accuracy of 90% when segregating the waste into six distinct categories.

Shuang Wu et.al.[15] proposed to better promote garbage classification, machine learning models are used to discover and solve garbage classification problems. First, the factor analysis is used to conduct field investigation and data analysis on residents' perception of waste classification. Second, convolutional neural network (CNN) is used to classify and recognize garbage images, which is used to assist the judgment of garbage classification. We should put forward some reasonable classification suggestions to better promote the problem of garbage classification.

Jenil Kanani et.al.[16] proposes a novel approach inspired by pixel distribution learning techniques to enhance automated garbage classification. The method aims to address limitations of conventional convolutional neural network (CNN)-based approaches, including computational complexity and vulnerability to image variations. The exponential growth in waste production due to rapid economic and industrial development necessitates efficient waste management strategies to mitigate environmental pollution and resource depletion.

P. Nagaraj et.al.[17] proposed to develop a smart sterile management system using a Tensor Flow-based deep learning model. In real time, it recognizes and categorizes items. Metal, plastic, and paper waste are separated from other sorts of trash in the bin's several divisions. Object detection and garbage classification are carried out using the Tensor Flow framework and a trained object recognition model. In order to create a frozen inference graph that can be used to recognize things using a camera, this trash detection model is trained on garbage photographs.

Megha Chhabra et.al.[18] proposed work uses Improved Deep Convolutional Neural Network (DCNN). The dataset of 2 class category with 25077 images is divided into 70% training and 30% testing images. The performance metrics used are classification Accuracy, Missed Detection Rate (MDR), and False Detection Rate (FDR). The results of Improved DCNN are compared with VGG16, VGG19, MobileNetV2, DenseNet121, and EfficientNetB0 after transfer learning. Experimental results show that the image classification accuracy of the proposed model reaches 93.28%.

I. N. Abood et.al [19] proposed that waste is the total remnants of domestic, agricultural, industrial and productive human activities, all the trash left somewhere, the neglect of which threatens and harms public safety. Waste is divided into many types such as: Non-biodegradable waste, Hazardous waste, Industrial waste, Municipal solid waste, Agricultural waste. The efficiency and accuracy of conventional trash classification techniques are both low, Waste classification is the process of identifying and categorizing different types of waste based on their characteristics. Accurate waste classification is important for a number of reasons, including supporting recycling and other forms of resource recovery, protecting the environment and human health, and reducing the costs of waste management.

H. Abu-Qdais et.al. [20] develop an automated waste classification model by testing traditional and deep machine learning models. To achieve that, both open and generated datasets were used in the model training and testing. The study results showed relatively low prediction capability of the traditional machine learning models like Random Forest (RF) and Support Vector Machine (SVM) as compared to the deep machine learning Convolutional Neural Network (CNN). The testing of the three models on a combined data set of Trashnet with local garbage data set resulted in accuracy of 62.5% for SVM, 72.0% for RF and 92.7% for CNN. JONET deep learning model has been developed using a combination of pre-trained base model (DenseNet 201) with a new architecture that contains a fully connected layer in the classification stage with 1024 neurons. The model is capable to identify six classes of solid waste items with various accuracies. When tested on the Trashnet dataset, the accuracy was 96.06%, while testing on the local garbage dataset gave an accuracy of 94.40%.

## 3. SYSTEM DESIGN AND IMPLEMENTATION:

### 3.1 System Design:

The proposed framework for garbage classification of waste images is defined as shown in figure 3.1.

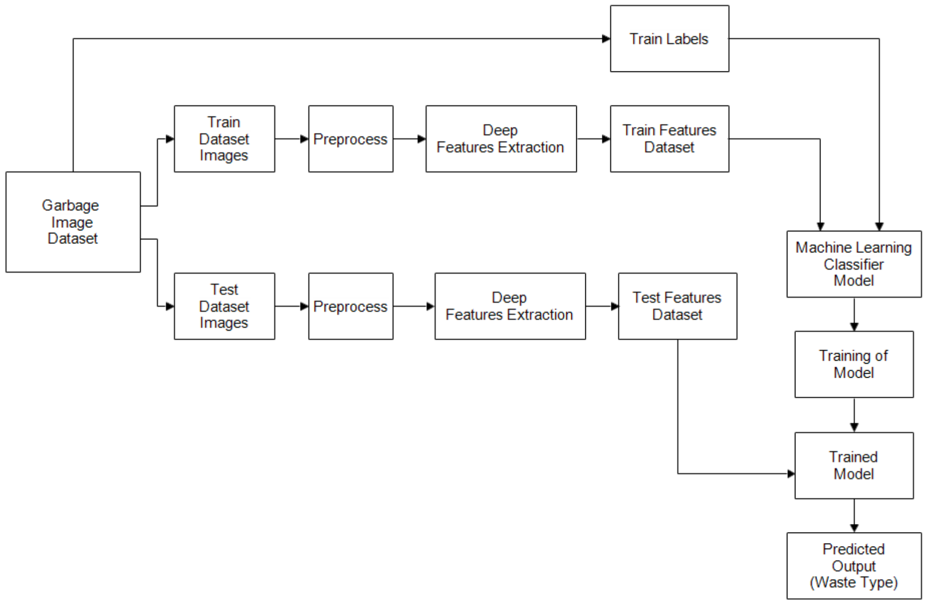



**Fig 3.1: Garbage Classification Framework**

#### 3.1.1. Dataset:

In proposed work, the Trashbox standard benchmark dataset from Kaggle ((https://www.kaggle.com/datasets/minhle13/trashbox)) used, which tailored for tasks like garbage classification and recycling management systems. It is widely used in developing machine learning models for identifying and classifying various types of waste, enabling advancements in environmental sustainability and smart waste sorting systems. It includes high-resolution images of various waste categories, such as cardboard, e-waste, glass, medical, metal, paper, and plastic with annotations for each type. Trashbox plays a critical role in creating AI-powered solutions for recycling, smart bins, and automated waste segregation, contributing to sustainable environmental practices. The dataset has collection of total 1400 images, which later splitting into 80-20% train and test ratio. The training dataset has 160 images for each class totaling the overall training dataset size to 1120 images. The test set is made up of 40 images for each class totaling up to 280 images. The quantity of images for all classes in all 7 sets are balanced.

#### 3.1.2. Preprocessing:

Feature engineering for a dataset of waste images labeled with classes involves extracting meaningful features from the images that can be used to train machine learning or deep learning models. In this context, image preprocessing and feature extraction are the key component operations. Resize the Images: Image resizing changes the dimensions of an image, either to scale it up or down, which is essential in tasks like image preprocessing for machine learning, display optimization, and file size reduction. MATLAB provides straightforward tools for resizing images. Normalize the image dimensions to ensure consistency across the dataset (e.g., resize all images to 224x224 pixels).

#### 3.1.3. Feature Extraction:

Feature extraction is the preliminary step in image classification. Sometimes the input data size is too large, which is tremendously hard to procedure in its raw form. For solving this, the input data can be transformed into a set of features. Feature extraction is the method by which unique features of skin lesion images are extracted. This method reduces the complexity in classification problems. The purpose of feature extraction is to reduce the original data set by measuring certain properties, or features, that distinguish one input pattern from another. At the next stage, a collection of important features gets extracted from the segmented image namely pixel mean intensity and diameter. The pre-trained Deep CNN models are used to extract the features from an image. It loaded with weights from ImageNet and configured to exclude their fully connected layers, retaining only the convolutional layers. The waste images are passed through each model to extract deep convolutional features, which represent high-level patterns in the images.

**3.1.4. Classification:**

Classifier is used to classify waste images into type of its category. To classify feature data into a given number of classes, we have used machine learning technique. In this project, the multi kernel Support Vector Machine (MK-SVM) classifier and Random Forest classifier, are used to train the images. Then, the classification of images will be carried out using machine learning classification model which finally provides the output as classified images. Training and testing of proposed classification models for classifying waste images using classification model will be done in proposed approach. MATLAB R2021b is used for simulation purposes. The process of extracting features takes place using MATLAB and classifier operation is carried out utilizing machine learning toolbox. The applied toolbox helps to develop the trained prediction approaches from the filtered features in an easier way and rapid way.

**3.2 IMPLEMENTATION:**

**3.2.1. Feature Extraction:**

Inception V3 is a deeper and more complex network designed to capture multi-scale features through its inception modules. Inception-v3 is a pre-trained convolutional neural network that is 48 layers deep, which is a version of the network already trained on more than a million images from the ImageNet database. This pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 299-by-299. The model extracts general features from input images in the first part and classifies them based on those features.

Inception v3 mainly focuses on burning less computational power by modifying the previous Inception architectures. This idea was proposed in the paper Rethinking the Inception Architecture for Computer Vision, published in 2015. It was co-authored by Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, and Jonathon Shlens. In comparison to VGGNet, Inception Networks (GoogLeNet/Inception v1) have proved to be more computationally efficient, both in terms of the number of parameters generated by the network and the economical cost incurred (memory and other resources). If any changes are to be made to an Inception Network, care needs to be taken to make sure that the computational advantages aren't lost. Thus, the adaptation of an Inception network for different use cases turns out to be a problem due to the uncertainty of the new network's efficiency. In an Inception v3 model, several techniques for optimizing the network have been put suggested to loosen the constraints for easier model adaptation. The techniques include factorized convolutions, regularization, dimension reduction, and parallelized computations.

**3.2.2. Inception v3 Architecture:**

The architecture of an Inception v3 network is progressively built, step-by-step, as explained below:

3.2.2.1 *Factorized Convolutions*: this helps to reduce the computational efficiency as it reduces the number of parameters involved in a network. It also keeps a check on the network efficiency.

3.2.2.2 *Smaller convolutions*: replacing bigger convolutions with smaller convolutions definitely leads to faster training. Say a 5 × 5 filter has 25 parameters; two 3 × 3 filters replacing a 5 × 5 convolution has only 18 (3*3 + 3*3) parameters instead. Since both 3x3 convolutions can share weights among themselves, the number of computations can be reduced.

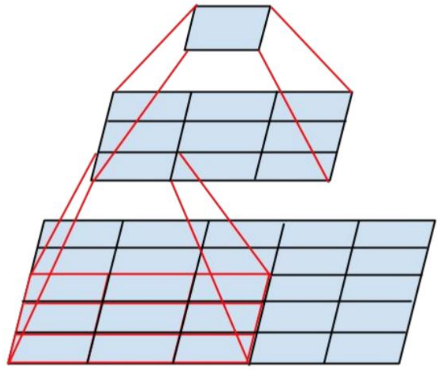


**Fig 3.1: 3x3 convolution with a fully-connected layer**

3.2.2.3 *Asymmetric convolutions*: A 3 × 3 convolution could be replaced by a 1 × 3 convolution followed by a 3 × 1 convolution. If a 3 × 3 convolution is replaced by a 2 × 2 convolution, the number of parameters would be slightly higher than the asymmetric convolution proposed.


**Fig 3.2: Filter Structure**

3.2.2.4 *Auxiliary classifier*: An auxiliary classifier is a small CNN inserted between layers during training, and the loss incurred is added to the main network loss. In Google Net auxiliary classifiers were used for a deeper network, whereas in Inception v3 an auxiliary classifier act as a regularizer.

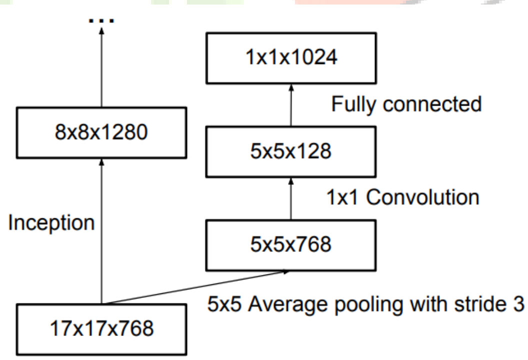



**Fig 3.3: Pooling Structure**

3.2.2.5 *Grid size reduction*: Grid size reduction is usually done by pooling operations. However, to combat the bottlenecks of computational cost, a more efficient technique is proposed:

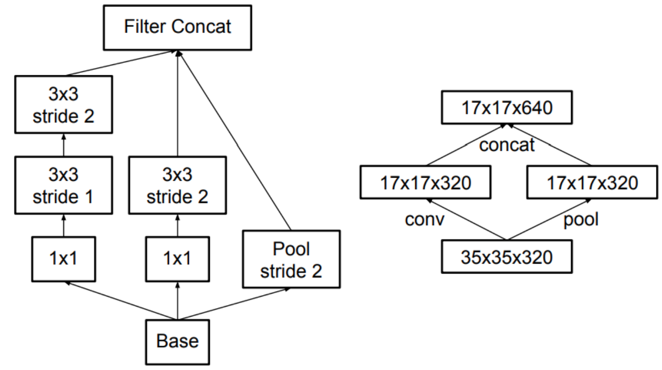



**Fig 3.4: Cascading Filter with Pooling Structure**

All the above concepts are consolidated into the final architecture.

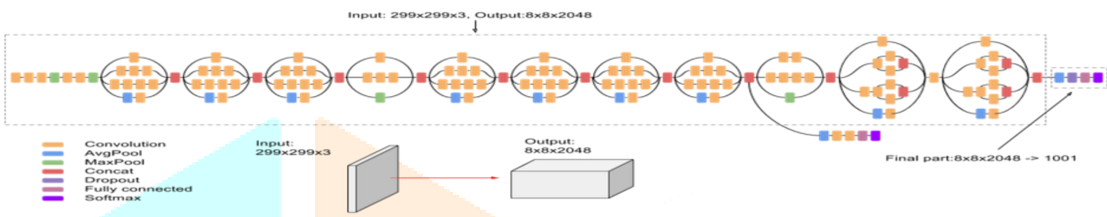



**Fig 3.5: Inception V3 architecture**

### 3.2.3. Classification:

#### 3.2.3.1 Random Forest (RF):

Ensemble Bagging Classifier, also known as Bootstrap Aggregating, is a powerful ensemble learning technique that combines the predictions from multiple models to improve the overall performance of the classifier. Bagging helps to reduce the variance of the model by averaging the predictions of the individual models, making it more robust and less prone to overfitting. Multiple subsets of the original training data are created by randomly sampling with replacement. Each of these subsets is used to train a separate base model (often called a "weak learner"). Because the samples are drawn with replacement, some data points may appear in multiple subsets, while others may be excluded from certain subsets. Each of the bootstrapped datasets is used to train a different model. The models can be of any type, but decision trees are commonly used in bagging. These models are trained independently and in parallel. After training, the predictions from all the individual models are aggregated. For classification tasks, the aggregation is typically done using majority voting, where the class that receives the most votes from the models is selected as the final prediction. In regression tasks, the predictions are averaged. The final output of the bagging ensemble is the result of the aggregation process. Because the individual models are trained on different subsets of the data, bagging tends to reduce variance and helps to avoid overfitting, leading to a more stable and accurate model.

Random Forest is a popular ensemble learning method used for classification (and regression) tasks. It operates by constructing a multitude of decision trees during training and outputs the class that is the mode of the classes predicted by individual trees. It's robust to overfitting, effective for large datasets, and handles high-dimensional spaces well. Random Forest algorithm is a powerful tree learning technique in Machine Learning. It works by creating a number of Decision Trees during the training phase. Each tree is constructed using a random subset of the data set to measure a random subset of features in each partition. This randomness introduces variability among individual trees, reducing the risk of overfitting and improving overall prediction performance.

In prediction, the algorithm aggregates the results of all trees, either by voting (for classification tasks) or by averaging (for regression tasks) This collaborative decision-making process, supported by multiple trees with their insights, provides an example stable and precise results. Random forests are widely used for classification and regression functions, which are known for their ability to handle complex data, reduce overfitting, and provide reliable forecasts in different environments. Figure 3.10 depicts the principle of random forest classification.

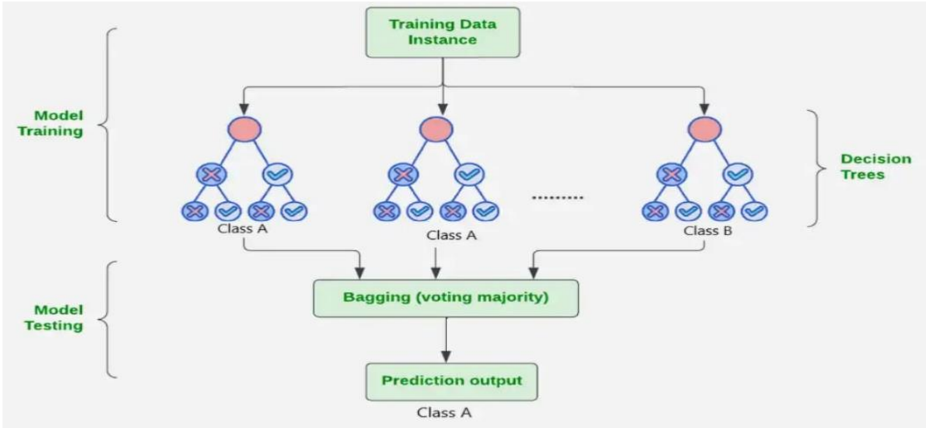



**Fig 3.6: Principle of Random Forest Classification**

The random forest algorithm works in several steps which are discussed below:

1. *Ensemble of Decision Trees:* Random Forest leverages the power of ensemble learning by constructing an army of Decision Trees. These trees are like individual experts, each specializing in a particular aspect of the data. Importantly, they operate independently, minimizing the risk of the model being overly influenced by the nuances of a single tree.
2. *Random Feature Selection:* To ensure that each decision tree in the ensemble brings a unique perspective, Random Forest employs random feature selection. During the training of each tree, a random subset of features is chosen. This randomness ensures that each tree focuses on different aspects of the data, fostering a diverse set of predictors within the ensemble.
3. *Bootstrap Aggregating or Bagging:* The technique of bagging is a cornerstone of Random Forest's training strategy which involves creating multiple bootstrap samples from the original dataset, allowing instances to be sampled with replacement. This results in different subsets of data for each decision tree, introducing variability in the training process and making the model more robust.
4. *Decision Making and Voting:* When it comes to making predictions, each decision tree in the Random Forest casts its vote. For classification tasks, the final prediction is determined by the mode (most frequent prediction) across all the trees. In regression tasks, the average of the individual tree predictions is taken. This internal voting mechanism ensures a balanced and collective decision-making process.

### 3.2.3.2 Support Vector Machine (SVM):

The Support Vector Machine (SVM) extends the traditional Support Vector Machine (SVM) that leverages multiple kernel functions to improve the model's performance and flexibility. In traditional SVM, a single kernel function transforms the input data into a higher-dimensional space where a hyperplane can separate the classes. SVM, on the other hand, uses a combination of multiple kernels to capture different aspects of the data, providing a more nuanced transformation and potentially better performance. In SVM, multiple kernel functions are used, each capturing different features or patterns in the data. The combination of these kernels allows the model to adapt to various data characteristics. Each kernel function is assigned a weight, and the overall kernel used in SVM is a weighted sum of these individual kernels. The model learns these weights during training to optimize the performance.

Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression tasks, although it is primarily applied to classification. SVM aims to find the optimal hyperplane that maximally separates different classes in the feature space. SVMs are particularly effective because they focus on finding the maximum separating hyperplane between the different classes in the target feature, making them robust for both binary and multiclass classification. In this outline, we will explore the Support Vector Machine (SVM) algorithm, its applications, and how it effectively handles both linear and nonlinear classification, as well as regression and outlier detection tasks.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which two different categories are classified using a decision boundary or hyperplane:

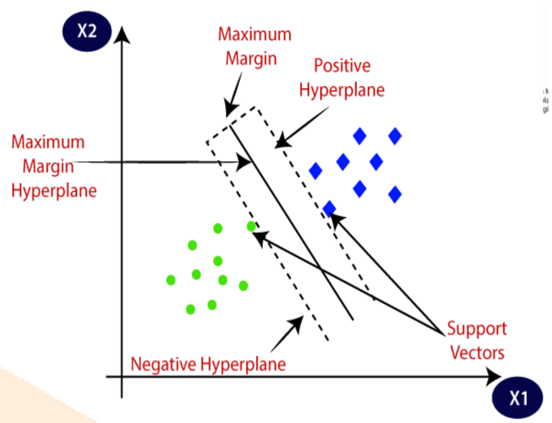



**Fig 3.7: Principle of Support Vector Machine Classification**

The support vector machine algorithm works in several steps which are discussed below:

1. *Split the data:* As with other machine learning models, start by splitting your data into a training set and testing set.
2. *Generate and evaluate the model:* Train the training samples on the classifier and predict the response. Evaluate performance by comparing accuracy of the test set to the predicted values.
3. *Hyperparameter tuning:* Hyperparameters can be tuned to improve the performance of an SVM model.

**3.2.3.3. Support Vectors:**

The data points or vectors that are the closest to the hyperplane and which affect the position of the hyperplane are termed as Support Vector. Since these vectors support the hyperplane, hence called a Support vector.

**3.2.3.4. How does SVM works?**The working of the SVM algorithm can be understood by using an example. Suppose we have a dataset that has two tags (green and blue), and the dataset has two features x1 and x2. We want a classifier that can classify the pair (x1, x2) of coordinates in either green or blue. Consider the below image:

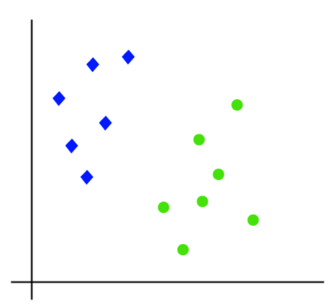


**Fig 3.8: plot of feature vectors in 2d space**

So, as it is 2-d space so by just using a straight line, we can easily separate these two classes. But there can be multiple lines that can separate these classes. Consider the below image:

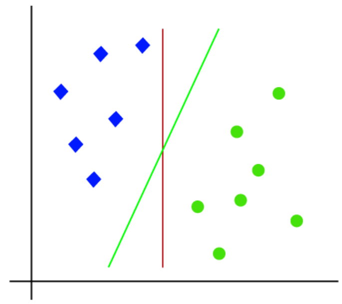


**Fig 3.9: plot of hyperplane with feature vectors**

Hence, the SVM algorithm helps to find the best line or decision boundary; this best boundary or region is called as a hyperplane. SVM algorithm finds the closest point of the lines from both the classes. These points are called support vectors. The distance between the vectors and the hyperplane is called as margin. And the goal of SVM is to maximize this margin. The hyperplane with maximum margin is called the optimal hyperplane.

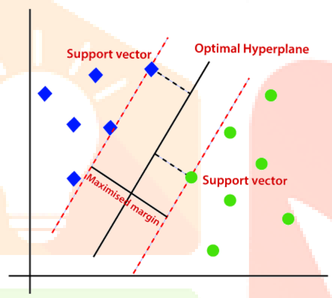



**Fig 3.10: plot of support vector with hyperplane**

### 3.2.4. MATLAB Software:

MATLAB is a matrix-based language. Since operations may be performed on each entry of a matrix, “for” loops can often be bypassed by using this option. As a consequence, MATLAB programs are often much shorter and easier to read than programs written for instance in C or FORTRAN. Matlab is a software program that allows doing data manipulation and visualization, calculations, math and programming. It can be used to do very simple as well as very sophisticated tasks. Matlab is a high-performance language for technical computing. Matlab is useful because it simplifies the analysis of mathematical models, it frees you from coding in high-level languages (saves a lot of time - with some computational speed penalties), provides an extensible programming/visualization environment, provides professional looking graphs. In our proposed system we will be using Image processing toolbox due to its user-friendly nature.

#### *3.2.4.1. Typical Uses of MATLAB*

a. Mathematical computations

b. Algorithmic development

c. Model prototyping (prior to complex model development)

d. Data analysis and exploration of data (visualization)

e. Scientific and engineering graphics for presentation

Complex analysis using MATLAB toolboxes (i.e., statistics, neural networks, fuzzy logic, H-infinity control, economics, etc.)

### *3.2.4.2. MATLAB Environment*

Matlab is a software program that allows you to do data manipulation and visualization, calculations, math and programming. It can be used to do very simple as well as very sophisticated tasks. We will start very simple. The name 'Matlab' comes from two words: matrix and laboratory. According to The Math Works (producer of Matlab), Matlab is a technical computing language used mostly for high-performance numeric calculations and visualization. It integrates computing, programming, signal processing and graphics in easy-to-use environment, in which problems and solutions can be expressed with mathematical notation. Basic data element is an array, which allows for computing difficult mathematical formulas, which can be found mostly in linear algebra. But Matlab is not only about math problems. It can be widely used to analyze data, modeling, simulation and statistics. Mat-lab high-level programming language finds implementation in other fields of science like biology, chemistry, economics, medicine and many more. Most important feature of Matlab is easy extensibility. This environment allows creating new applications and becoming contributing author. It has evolved over many years and became a tool for research, development and analysis. Matlab also features set of specific libraries, called toolboxes. They are collecting ready to use functions, used to solve particular areas of problems. Matlab System consist of five main parts.

### *3.2.4.3. Computing Toolbox*

Matlab offers very wide selection of toolboxes. Most of them are created by Math works but some are made by advanced users. There is a long list of possibilities that this program gives. Starting from automation, through electrical engineering, mechanics, robotics, measurements, modeling and simulation, medicine, music and all kinds of calculations. Next couple of paragraphs will shortly present some toolboxes available in Matlab. The descriptions are based on the theory from Mrozek & Mrozek (2001, 387 – 395) about toolboxes and Mathworks.com. Image processing toolboxes and Map-ping Toolbox is one of which is responsible for analyzing geographic data and creating maps. It provides compatibility for raster and vector graphics which can be imported. Additionally, as well two-dimensional and three-dimensional maps can be displayed and customized. It also helps with navigation problems and digital terrain analysis. Image Acquisition Toolbox is a very valuable collection of functions that handles receiving image and video signal directly from computer to the Matlab environment. This toolbox recognizes video cameras from multiple hardware vendors. Specially designed interface leads through possible transformations of images and videos, acquired thanks to mechanisms of Image Acquisition Toolbox. Statistics and Machine Learning Toolbox provides functions and apps to describe, analyze, and model data. You can use descriptive statistics, visualizations, and clustering for exploratory data analysis; fit probability distributions to data; generate random numbers for Monte Carlo simulations and perform hypothesis tests. Regression and classification algorithms let you draw inferences from data and build predictive models either interactively, using the Classification and Regression Learner apps, or programmatically, using AutoML.

## 4. RESULT AND DESCUSSION:

### 4.1. Experimental Setup:

The proposed system is implemented and analyzed on Intel CORE processor i3, 8GB RAM Laptop configuration, and Windows 10 operating system. MATLAB R2021b Software is used to write the programming code in this we used Image processing and Statistics and Machine Learning toolbox. The images used to train and test are used from the Kaggle, Thrashbox benchmark Dataset for experimentation analysis.

### 4.2. Evaluation Measures:

Performance evaluation metrics are essential for assessing the effectiveness of machine learning models, particularly in classification, regression, and other predictive tasks. Different metrics suit different types of problems, so selecting the right ones helps interpret the model's accuracy, robustness, and generalizability. Below are some of the common performance evaluation parameters:

*Confusion Matrix:* It contains information about actual and predicted classifications done by a classification system. The performance of such systems is commonly evaluated using the data in the matrix.

*Accuracy:* The proportion of correctly classified instances (both positive and negative) among the total number of instances. A high accuracy indicates that the model is correctly identifying both diseased and healthy cases most of the time.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

*Precision:* The proportion of true positive predictions among all positive predictions. Precision reflects the accuracy of the model in identifying true positive cases (correctly identifying the disease).

$$\text{Precision} = \frac{TP}{TP + FP}$$

*Recall:* The proportion of true positive cases that are correctly identified by the model. Recall measures the model's ability to detect all actual positive cases (diseased patients).

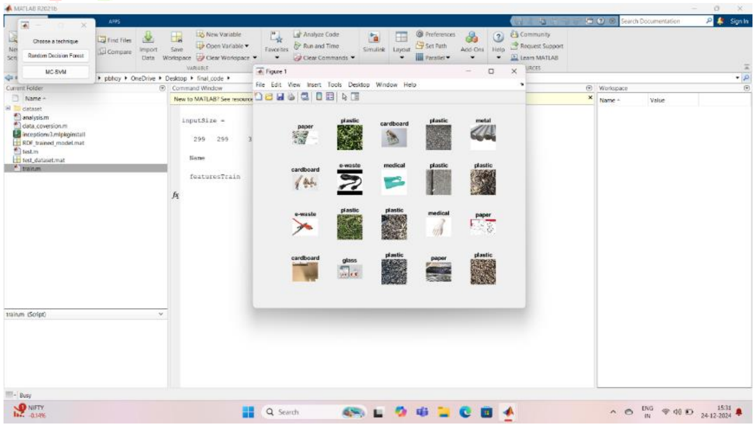
$$\text{Recall} = \frac{TP}{TP + FN}$$

*F1-Score:* The harmonic means of precision and recall, providing a single metric that balances both concerns. The F1-score is useful when the class distribution is imbalanced, offering a more balanced view than accuracy.

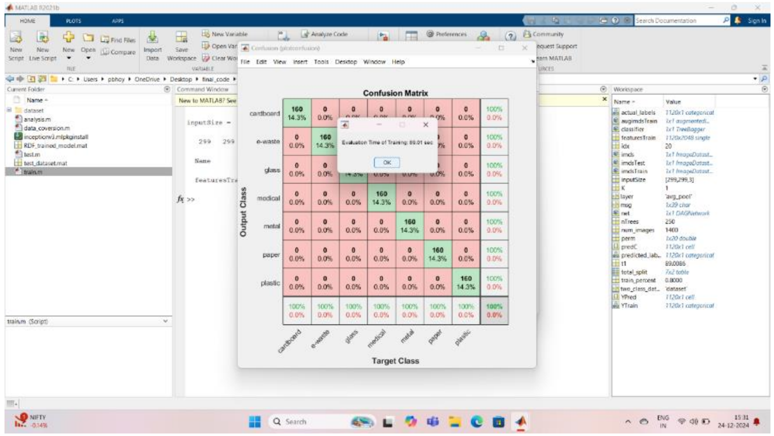
$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

**4.3. Result evaluation:**

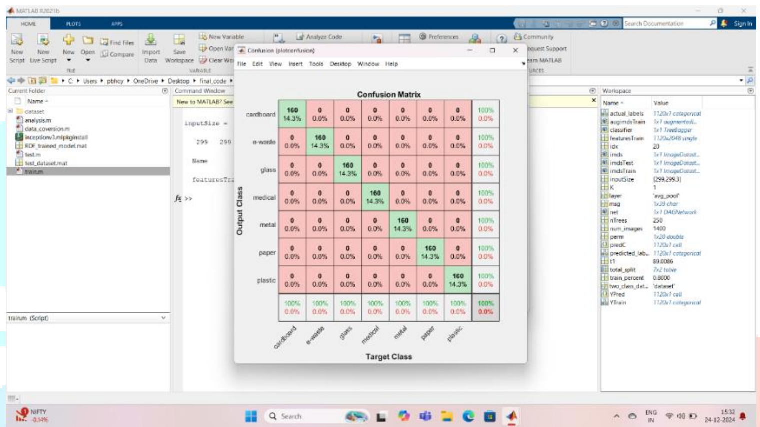
**4.3.1] Training Phase:**



**Screenshot 4.1: Input Dataset**



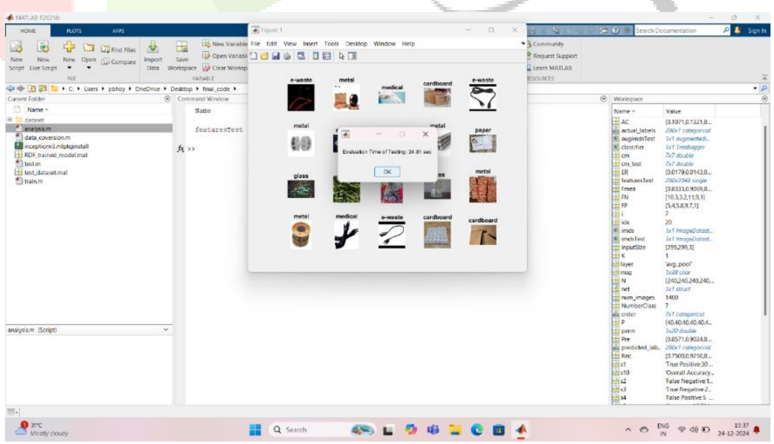

Screenshot 4.2: Evaluation time of training



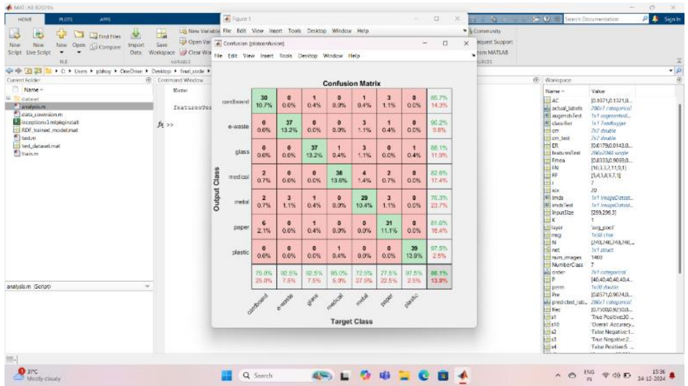

Screenshot 4.3: Confusion matrix of training

In this confusion matrix we can see that for each category we have considered 160 images to train the model in the target class category and get 100% accuracy for output class for training. In this confusion matrix, the given target class and predicted output class has been verified successfully using artificial neural network.

**4.3.2] Analysis Phase:**

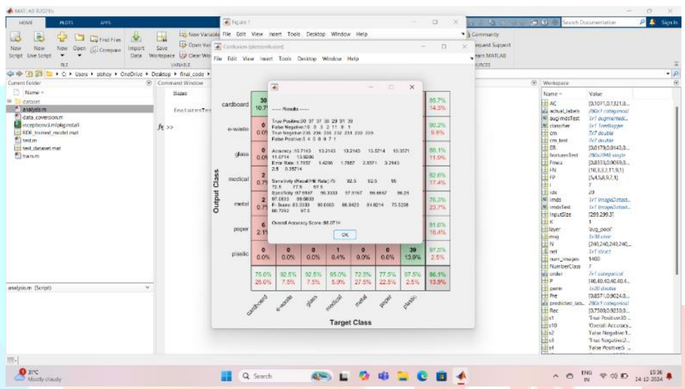


Screenshot 4.4: Evaluation time of testing




**Screenshot 4.5: Confusion Matrix of testing**

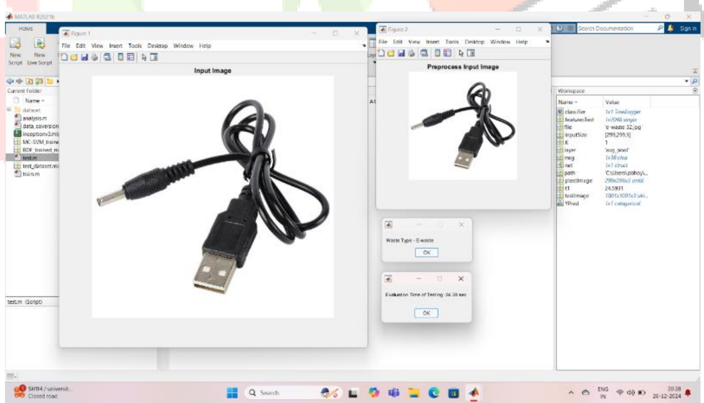
In confusion matrix, for target class we can see that for each category we have consider 40 images out of which we get 86.1% overall accuracy for the testing of trained model and 13.9% misconfigured data.



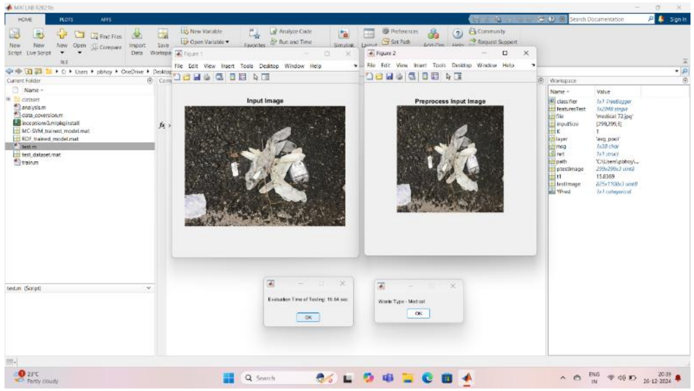

**Screenshot 4.6: Result of evaluation of training parameter**

Here, we have calculated accuracy, recall rate, precision and F-1 score with the help of standardized formulae for each category of waste image. So, the overall accuracy of our classification model is 86.07%.

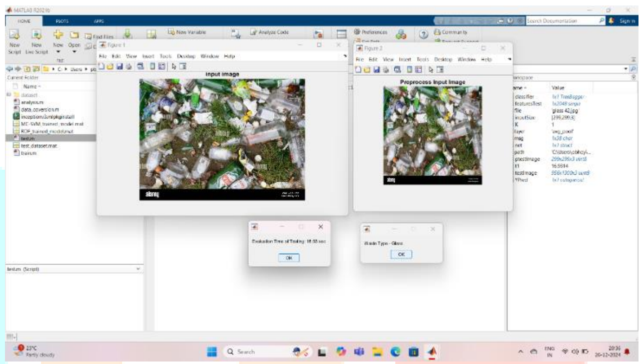
**4.3.3] Testing Phase:**




**Screenshot 4.7: Identified E-waste**



**Screenshot 4.8: Identified Medical Waste**



**Screenshot 4.9: Identified Glass waste**

From the above screenshot it is observed that we have classified the waste images in the E-waste, medical and glass categories individually with the evaluation time of testing.

### 4.3.4.] Comparison of model based on accuracy:

| Researchers | Technology used | Accuracy |
|---|---|---|
| Olugboja Adedeji et.al. | RestNet-50 and SVM | 87% |
| S. Varudandi et.al. | IoT and Machine learning | 75% |
| H. Abu-Qadis et.al. | JONET deep learning model | 94% |
| J. Shah et.al. | Deep learning algorithm | 94% |
| Proposed work | Hybrid model (DL and ML) | 86.01% |

## 5. ADVANTAGES:

Garbage classifier offers several advantages including reducing labor input, enhancing classification accuracy and efficiency, promoting resources recycling, and reducing environmental pollution. This technology holds significant promise for urban management, environmental protection, and sustainable development.

1. Improved Accuracy: It achieves high precision in identifying and categorizing waste, minimizing subjective human judgement, and enhancing accuracy and consistency in classification.

2. Enhanced Efficiency: The system handles a large volume of waste in short time, boosting efficiency. Compared to traditional manual sorting, this automated process saves time and human resources.

3. Reduced Labor Costs: This system reduces the reliance on human labor, thus lowering operational costs for city management organizations and waste disposal companies.

## 6. CONCLUSION:

We proposed a waste classification system that is able to separate different components of waste using the Machine learning tools. This system can be used to automatically classify waste in seven categories that are cardboard, medical, e-waste, glass, metal, paper, plastic and help in reducing human intervention and preventing infection and pollution. From the result, when tested against the trash dataset, we got an accuracy of 87%. The separation process of the waste will be faster and intelligent using our system without or reducing human involvement. If more image is added to the dataset, the system accuracy can be improved. In the future, we will tend to improve our system to be able to categories more waste item, by turning some of the parameters used.

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