Recyclable Waste Classification using SquezeeNet and XGBoost

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***Abstract*—The unregulated buildup of waste results in the occurrence of flames. This phenomenon poses a substantial threat to both the ecological system and human welfare. To tackle this problem, the current study proposes the implementation of Machine Learning technology to automate the sorting of waste. The methodology being examined incorporates the utilization of SqueezeNet as an image embedding method in conjunction with XGBoost as the final classifier. This work examines the efficacy of the aforementioned technique by doing a comparative analysis with many alternative final classifiers, including LightGBM, XGBoost, CatBoost, Random Forest, SVM, Naïve Bayes, KNN, and Decision Tree. The experimental results indicate that the integration of SqueezeNet and XGBoost produces the highest level of performance in the field of garbage categorization, as supported by an F1-score of 0.931. SqueezeNet is a method employed for image embedding that enables the extraction of salient features from images. This procedure enables the recognition of unique characteristics linked to different classes. Therefore, XGBoost may be utilized to enhance classification tasks. XGBoost has the ability to generate a feature importance score. Therefore, enabling the recognition of the most prominent attributes. This methodology possesses the capacity to alleviate the risk of fire that arises due to the accumulation of unregulated trash. This work makes a substantial contribution to environmental conservation and the improvement of public safety.**

***Keywords*—Garbage classification; image; machine learning; SqueezeNet; XGBoost**

I. Introduction

Landfill fires are caused by human and environmental factors [1]. Uncontrolled burning causes flames. When heated, plastic, paper, and biological materials can catch fire. Due to the high population, a fire from a pile of waste spreads quickly and uncontrollably, making containment difficult. Chemical reactions can occur in hot and humid situations [2], [3], especially in areas where organic waste decomposes, generating heat and fire-starting gases. Fermentation and breakdown can produce methane. Direct sunlight and extreme temperatures can heat gathered rubbish [4-5]. The risk of fire increases when waste contains combustible materials. When mixed, hazardous trash like solvents, batteries, and other poisons can create heat or burn. Sometimes exterior fires, maybe caused by humans, enter the building. For instance, illegally incinerated garbage [6-8] or environmental components like embers from nearby forest fires. These sites release toxic gases like methane. In the presence of an igniting source and a gas leak, a fire may occur. Environmental factors including high winds and severe weather might affect fire growth [9–11]. Strong winds may help a fire spread quickly. Fires in this area harm the environment, health, and infrastructure. Thus, garbage segregation and other waste management measures are crucial.

The field deployment of garbage segregation has numerous hurdles that may hinder waste management programs [12–14]. Public comprehension of waste segregation and its environmental benefits is sometimes lacking. Educational and socialization efforts are needed to raise awareness of waste segregation. Additionally, many places lack the capacity to segregate trash. Without separate receptacles, recycling infrastructure, and clear instructions, waste segregation may be difficult. Trash segregation by communities may not guarantee long-term landfill diversion without proper recycling facilities. Without recycling facilities, rubbish sorting may be less appealing. Insufficient or inaccurate waste sorting may reduce sorting efficiency. Recycling is difficult when separated items are mixed together.

Efficient and effective waste segregation technology has several benefits for waste management and environmental preservation. Advanced sorting technology can precisely separate various materials. Segregating materials improves recycling efficiency and produces higher-quality products. By using good segregation technology, landfill garbage may be reduced [15]. This approach extends landfill life and reduces habitat damage. Effective waste segregation reduces environmental deterioration, especially soil and water pollution. Sorting technology separates pollutants to protect ecosystems and human health. Manual sorting is laborious and error-prone. Sorting technology can improve material separation and save manual labor, solving the problem.

Technology has improved segregation precision and consistency, exceeding hand sorting. Organic trash, including food scraps, leaves, and other biodegradable materials, may be distinguished from recyclable garbage like plastic, paper, and metal with great precision [16–21]. Implementing waste separation techniques requires a categorization system that can independently distinguish organic and recyclable components. The merging of computer vision and artificial intelligence (AI) has improved rubbish categorization precision and efficacy [22]. The seamless integration of these two sophisticated technologies allows the system to independently identify and classify waste items. Computer vision is an academic field that lets computers view and understand visual data like images and movies like humans [23-27]. Computer vision systems can recognize trash items' unique traits. Advanced cameras and optical sensors enable discernment by effectively examining and interpreting color, shape, and texture. Additionally, it shows the capacity to critically evaluate a variety of visual representations and data from different angles. A powerful image processing algorithm allows the system to distinguish patterns, characteristics, and qualities that distinguish organic from recyclable trash. Artificial intelligence, especially machine learning, is crucial to trash categorization.

Machine learning algorithms may learn from training data, allowing them to recognize and understand patterns and make accurate classification judgments [28]. Computer vision and AI require model training for categorization. This complex procedure uses massive quantities of sample images and waste material data. By using many samples, the model can identify biological waste from recyclable waste. The trained model can automatically and instantly categorize garbage after training. The process uses a camera or optical sensor to capture an image of the garbage. An artificial intelligence algorithm then analyzes the image and accurately classifies the garbage.

Convolutional Neural Networks (CNNs) are highly effective in processing image data [29–31]. This neural network uses convolutional layers to identify complex visual properties from a garbage image and categorize it by kind. Large amounts of data are needed to train CNN models. However, training data is sometimes limited, especially for specialized or rare image recognition assignments. To overcome deep neural network model training challenges, transfer learning in CNNs has become a feasible option. Transfer learning lets you use pre-trained models on large datasets to solve new problems using small datasets. Training multi-layer deep CNN models requires a lot of time, computer resources, and complex optimization methods. Transfer learning is a popular machine learning approach that uses pre-trained models to speed up model training. Using an existing model as a starting point reduces the time and computing resources needed to train a model from scratch.

SqueezeNet, a neural network architecture designed for image recognition, contains fewer parameters than AlexNet, VGG, and ResNet [32-34]. The SqueezeNet framework develops models with low parameter counts and great image recognition accuracy. SqueezeNet extracts visual features, which other approaches use as embedding representations. SqueezeNet embeds images by condensing visual input into numbers. This altered representation can help machine learning systems classify rubbish.

Bai studied garbage classification [35]. Machine vision, item recognition, and check categorization are performed sequentially. The hierarchical system development framework uses Struts2, spring, and Hibernate. Optical identification, convolutional neural networks, and Naive Bayes are crucial garbage categorization technologies. Ghanshala et al. use machine learning to categorize areas into two categories: garbage-free and high-garbage-filled [36]. The study used four algorithms, achieving 98.6% accuracy with kNN and Naïve Bayes, 85.4% with Decision Tree, and 98.4% with Random Forest.

Another classification has been done using Histogram of Oriented Gradients (HOG) features and an SVM boosting algorithm [37]. The submitted image is preprocessed to improve recognition. A HOG is used to extract properties. The classification device is trained to send relevant data to the image set. From this premise, the categorization scenario is identified. The algorithm's classification accuracy is 95% or better, a 10% improvement over the single SVM classification strategy. The garbage classification method is accurate and practical.

The current work suggests utilizing XGBoost as the final classifier once SqueezeNet features are generated. XGBoost, or Extreme Gradient Boosting, is a popular categorization machine learning approach. The ensemble technique combines predictions from numerous simpler machine learning models, known as "weak learners," to improve accuracy and resilience. The system automatically identifies and categorizes various waste materials into two classes (organic, and recyclable) using these two advanced technologies.

II. Material and Methods

The approach employed in the present study can be seen in Fig. 1. Furthermore, this study not only implemented the suggested method but also did a comparison with alternative methods.

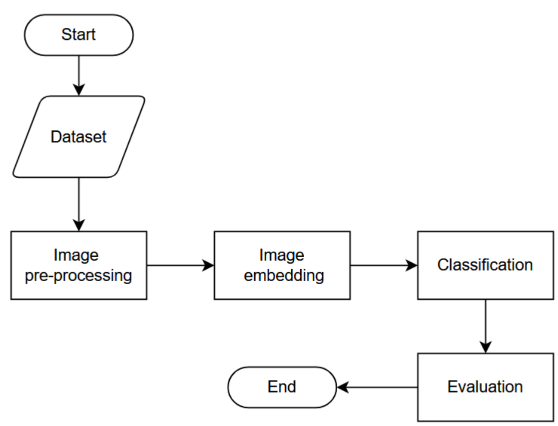

Fig. 1. Research methodology.

A. Dataset Collection

The dataset employed in this study was provided by Sashaank Sekar. The data may be accessed from the following source: https://www.kaggle.com/techsash/waste-classification-data. The initial dataset obtained from Kaggle has a total of 25,077 images, with 13,966 images depicting organic materials and 11,111 images representing recyclable materials. The images obtained are in the form of colored .jpg files, displaying a variety of portrait and landscape orientations. The resolution of these imagegraphs varies, with a minimum of 191 pixels and a high of 264 pixels.

B. SquzeeNet

SqueezeNet serves as a technique for producing image embeddings through the process of extracting features from images [31]. This stage involved running images through the convolution and pooling layers inside the SqueezeNet model, afterward extracting the output from one of these layers as a feature representation, also known as an embedding, of the image. The mechanism can be described as follows:

- Image preprocessing

It involves applying several techniques to prepare images in a dataset for further analysis. These techniques include pixel intensity normalization, resizing, and noise reduction, among others. The purpose of image preprocessing is to ensure that the images meet specific requirements and are ready for further analysis tasks.

- Feature extraction

It employs pre-processed images as the input data for the SqueezeNet architecture. The process involves passing images through convolutional and pooling layers inside the SqueezeNet architecture.

- Embedding layer

It designs a certain layer inside SqueezeNet as the desired location for extracting the feature representation (embedding) of the image. The inclusion of this layer is recommended prior to the implementation of the fully linked layers.

- Feature representation

It obtains feature representations involves passing images through the SqueezeNet architecture until a certain layer is reached, resulting in a vector representation of the image's features, also known as embeddings.

- Feature vectors

The vector can serve as image embeddings by utilizing the feature representation vectors derived from the preceding stage. These vectors were utilized as input in XGBoost, to perform the classification task.

C. XGBoost

XGBoost, also known as Extreme Gradient Boosting, is a commonly employed machine learning method that is particularly recognized for its effectiveness in classification problems [38-40]. The method in issue can be classified as a type of ensemble learning technique, wherein the outcomes of several smaller and less powerful models are combined to create a more robust model. XGBoost places emphasis on employing decision trees as its foundational model, while integrating the principles of gradient boosting and regularized regression to get exceptional performance across diverse tasks. Fig. 2 illustrates a simplified version of XGBoost. The components of XGBoost are as follows:

- Decision Trees

The method employed as the fundamental model in XGBoost. A decision tree is a hierarchical arrangement comprising of nodes and branches, which symbolize decisions or predictions made at each node.

- Gradient Boosting

XGBoost employs an ensemble learning technique with gradient boosting methodology. Initially, a preliminary (suboptimal) model is constructed, often in the form of a basic decision tree. Subsequently, a subsequent model is constructed with the purpose of addressing the errors committed by its predecessor. This procedure is iteratively conducted, with particular attention on data points that demonstrate persistent prediction mistakes.

- Boosting

In the context of XGBoost, the model addition process involves the incremental inclusion of a new decision tree into the existing ensemble at each iteration. The proposed model aims to predict the residual, which refers to the difference between the observed target value and the current representation, based on the preceding model.

- Penalty and Regularization

The XGBoost algorithm incorporates regularization techniques to enhance the performance of the decision trees it constructs. The successful completion of this job is helped by the utilization of an objective function that integrates objective regression alongside a penalty function, often L1 or L2, to mitigate the problem of overfitting.

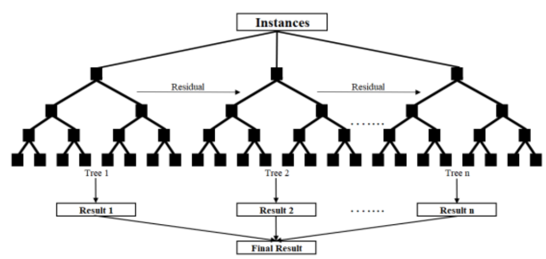

Fig. 2. Flowchart of XGBoost.

XGBoost possesses different benefits in comparison to other algorithms due to its unique operating mechanism. The XGBoost algorithm is a machine learning methodology that integrates regularization methods to effectively mitigate the problem of overfitting. The objective of this approach in this study was to develop models that demonstrate enhanced generalization and less sensitivity to the specific attributes of the training data. The XGBoost technique, which is widely used in machine learning, offers a wide range of hyperparameters that may be tuned to enhance the performance of the model. Furthermore, the failure to get the ideal value for the hyperparameter might be seen as an adverse result.

D. Evaluation

To optimize the evaluation process, it is imperative to partition the dataset into distinct subsets, namely a training set and a testing set [41]. The current study leveraged a dataset of considerable scale, thereby justifying the adoption of a five-fold cross-validation methodology. The utilization of cross-validation (CV) is a widely adopted methodology within the realm of machine learning for the purpose of evaluating the performance and effectiveness of prediction models [42]. The proposed methodology involves partitioning the provided dataset into multiple distinct subsets, commonly referred to as folds. This approach aims to assess the generalization capabilities of the model by simulating real-world scenarios where the model encounters novel data samples [43]. In each iteration of the experiment, a single fold is designated as the testing set, while the remaining four folds are allocated as the training set. In each iteration, it is imperative to compute the evaluation metric. Upon the completion of the five iterations, it becomes imperative to calculate the mean value of the evaluation metrics acquired throughout each iteration.

The present study incorporates a comprehensive set of evaluation metrics, namely accuracy, precision, recall, and the F1 score. The accuracy is computed by dividing the number of correctly classified instances by the total number of instances in the dataset. This ratio provides a clear representation of the model's ability to correctly classify data points. In such scenarios, relying solely on accuracy as an evaluation metric may introduce bias. The metric of precision is employed as a quantitative measure to evaluate the degree of accuracy exhibited by a model in generating positive predictions. The notion of recall is a fundamental aspect within the realm of machine learning, which concerns the model's capacity to effectively recognize and encompass all instances that are genuinely positive. The computation of the F1 score involves the utilization of the harmonic mean to combine accuracy and recall metrics. By calculating the harmonic mean of these two measures, the F1 score ensures a balanced evaluation, assigning equal importance to both accuracy and recall.

This study aim to conduct a comprehensive comparison between the SqueezeNet combination and an alternative final classifier, distinct from the widely used XGBoost algorithm. The objective is to evaluate the performance and efficacy of these two approaches in the context of machine learning. By undertaking this comparative analysis, it seek to shed light on the relative strengths and weaknesses of these methodologies, thereby contributing to the existing body of knowledge in the field of machine learning research. In the realm of machine learning, a multitude of algorithms have emerged as prominent contenders for various tasks. Among these algorithms, Random Forest, SVM with a Radial Basis Function (RBF) kernel, Naïve Bayes, K-Nearest Neighbor (KNN) with a value of K equal to 5, and Decision Tree have garnered significant attention and utilization. Random Forest, a versatile ensemble learning method, has proven to be highly effective in tackling classification and regression problems. By constructing a multitude of decision trees and aggregating their predictions, Random Forest mitigates overfitting and enhances generalization capabilities. SVM, a powerful algorithm for both classification and regression tasks, utilizes a kernel function to map data into higher-dimensional feature spaces. The RBF kernel, in particular, has exhibited remarkable performance in capturing complex relationships within data, enabling SVM to excel in diverse problem domains. Naïve Bayes, a probabilistic classifier, leverages Bayes' theorem with the assumption of feature independence. Despite its simplistic nature, Naïve Bayes has demonstrated remarkable efficiency and effectiveness, making it a popular choice for text classification and spam filtering tasks. KNN is a non-parametric algorithm that classifies data points based on the majority vote of their K nearest neighbors. With K set to 5, KNN strikes a balance between capturing local patterns and avoiding excessive noise, rendering it a valuable tool in pattern recognition and recommendation systems. In addition to the aforementioned Boosting variants, it is worth noting the existence of several other implementations in the field. Notably, two prominent examples are the Light Gradient Boosting Machine (LightGBM) and CatBoost, which both leverage the power of Gradient Boosting in conjunction with Decision Trees.

III. Results and Discussion

Tables I, II, and III provide a comprehensive overview of the performance metrics associated with the algorithms employed for the classification of organic, recyclable, and mixed wastes. The three tables demonstrate that the suggested method shows superior performance. The many variations of Boosting, including LightGBM, XGBoost, and CatBoost, exhibit superior performance with the K-Nearest Neighbors (KNN) algorithm.

TABLE I. THE AVERAGE PERFORMANCE OF EACH FINAL CLASSIFIER FOR THE "ORGANIC" CLASS DATA WAS EVALUATED

Final Classifier	**Accuracy**	**Precision**	**Recall**	**F1 Score**
LightGBM	0.912	0.917	0.926	0.921
XGBoost	0.931	0.935	0.942	0.939
CatBoost	0.925	0.931	0.934	0.932
Random Forest	0.893	0.890	0.922	0.906
SVM	0.706	0.672	0.924	0.778
Naïve Bayes	0.844	0.870	0.845	0.857
KNN	0.921	0.916	0.944	0.930
Decision Tree	0.859	0.866	0.884	0.875

The performance of the system achieved a score over 0.9 for all assessment parameters. Despite being lightweight convolutional neural network (CNN) architecture, SqueezeNet had remarkable proficiency in extracting features from image input. It implies that the features produced by SqueezeNet may possess greater informativeness and relevance compared to features provided by alternative models. Ensemble models, like LightGBM, XGBoost, and CatBoost, provide the ability to enhance overall performance by combining predictions from a limited set of basic models represented as decision trees.

TABLE II. THE AVERAGE PERFORMANCE OF EACH FINAL CLASSIFIER FOR THE "RECYCLABLE " CLASS DATA WAS EVALUATED

Model: R	**Accuracy**	**Precision**	**Recall**	**F1 Score**
LightGBM	0.912	0.906	0.894	0.900
XGBoost	0.931	0.926	0.918	0.922
CatBoost	0.925	0.917	0.913	0.915
Random Forest	0.893	0.897	0.857	0.877
SVM	0.706	0.819	0.433	0.567
Naïve Bayes	0.844	0.812	0.842	0.827
KNN	0.921	0.927	0.891	0.909
Decision Tree	0.859	0.850	0.829	0.839

TABLE III. THE AVERAGE PERFORMANCE OF EACH FINAL CLASSIFIER FOR ALL CLASS DATA WAS EVALUATED

Model: All	Accuracy	Precision	Recall	F1 Score
LightGBM	0.912	0.912	0.912	0.912
XGBoost	0.931	0.931	0.931	0.931
CatBoost	0.925	0.925	0.925	0.925
Random Forest	0.893	0.893	0.893	0.893
SVM	0.706	0.737	0.706	0.684
Naïve Bayes	0.844	0.844	0.844	0.844
KNN	0.921	0.921	0.921	0.920
Decision Tree	0.859	0.859	0.859	0.839

TABLE IV. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND LIGHTGBM MODELS

		Predicted	
		O	R
Actual	O	12936	1030
	R	1174	9937
	Total	14110	10967

TABLE V. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND XGBOOST MODELS

		Predicted	
		O	R
Actual	O	13150	816
	R	907	10204
	Total	14057	11020

Mechanisms such as boosting were employed to adaptively assign greater weight to samples that pose challenges in recognition, hence enhancing the system's capacity to effectively process intricate data. By engaging in mistake correction and prioritizing the analysis of challenging samples, individuals could enhance their proficiency in data classification. The utilization of secondary information obtained by decision trees in the boosting process is a common practice in boosting models. One potential approach is to incorporate the weight or score assigned to each tree in order to arrive at a conclusive determination. This intervention has the potential to enhance the overall efficacy of the model. The optimization of the parameters in this study led to the development of a model that effectively aligns with the observed data. The integration of SqueezeNet as a feature extractor with a boosting algorithm facilitated the combination of the robust feature extraction skills inherent in convolutional neural networks (CNNs) with the powerful ensemble capabilities offered by the boosting method. In contrast, the K-nearest neighbors (KNN) method employed in this work was classified as an instance-based approach, wherein the selection of K values determines the appropriate number of neighboring instances.

TABLE VI. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND CATBOOST MODELS

		Predicted	
		O	R
Actual	O	13042	924
	R	966	10145
	Total	14008	11069

TABLE VII. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND RANDOM FOREST MODELS

		Predicted	
		O	R
Actual	O	12876	1090
	R	1585	9526
	Total	14461	10616

TABLE VIII. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND SVM MODELS

		Predicted	
		O	R
Actual	O	12905	1061
	R	6300	4811
	Total	19205	5872

The utilization of SqueezeNet as a feature extractor for further application by classification models like Random Forest, Naïve Bayes, or Decision Tree encounters many obstacles that might potentially impact the performance of those models. CNN designs, such as SqueezeNet, often generate feature representations that possess quite large dimensions. The utilization of high-dimensional characteristics in models such as Random Forest, Naïve Bayes, or Decision Tree gives rise to a circumstance known as the "curse of dimensionality." This phenomenon implies that when the number of features is enormous, the potential sample space needed to generate accurate estimates grows much more expansive. Consequently, the models encounter difficulties in identifying pertinent patterns from the data, as evidenced by the findings of this study. The interdependence among the features produced by SqueezeNet is substantial, potentially leading to the confusion of outcomes in models that assume feature independence, such as Naïve Bayes. The performance of these models will be enhanced in cases when the characteristics exhibit a high degree of independence. The efficacy of a classification model is heavily influenced by the inherent attributes of the data employed. If the data has an apparent pattern that is more compatible with straightforward models or does not need very intricate feature representation, then models such as Random Forest, Naïve Bayes, or Decision Tree may be more appropriate. The intricate characteristics examined in this study were attributed as the underlying factor for the ineffectiveness of these algorithms non the categorization process. However, this was also due to the fact that these algorithms had not yet been calibrated with specific parameters.

TABLE IX. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND NAÏVE BAYES MODELS

		Predicted	
		O	**R**
Actual	O	11801	2165
	R	1759	9352
	Total	13560	11517

The study evaluated the performance of various machine learning methods. The Support Vector Machine (SVM) approach exhibited the lowest performance across all three tables. The attainment of precise classification frequently necessitates the inclusion of superior and discerning features. In the context of machine learning, it is imperative to ensure that the features extracted from a given model, such as SqueezeNet, effectively capture the salient and discriminative characteristics relevant to a specific task. Failure to achieve this may result in a detrimental impact on the performance of subsequent classification algorithms, such as Support Vector Machines (SVMs). The potential exists for SqueezeNet and Support Vector Machines (SVM) to demonstrate dissimilar scales in relation to the distribution of feature values. Introduction: In the context of machine learning, the issue of scaling mismatch has been identified as a potential challenge that can adversely affect the performance of Support Vector Machines (SVM). This research report aims to explore the difficulties that may arise due to scaling mismatch and the subsequent impact on the performance of SVM. Scaling Mismatch: Scaling mismatch refers to the situation where the scales of different features in a dataset are not aligned. In other words, the range or magnitude of values for different features varies significantly. This discrepancy in scaling can To mitigate the aforementioned concern, it is imperative to incorporate normalization or scaling methodologies. The performance of Support Vector Machines (SVMs) is significantly impacted by the selection of hyperparameters, which encompass the penalty parameter (C) and the kernel type. The observed suboptimal performance can potentially be attributed to the presence of inaccurate hyperparameter configurations. The impact of data type on the performance of Support Vector Machines (SVM) for model training was found to be statistically significant. The efficacy of Support Vector Machines (SVM) may be influenced by the congruity between the training data employed for generating the embedding and the data that necessitates categorization. The present study investigates the impact of SVM parameter values on its ability to handle complex data. The findings reveal that the utilization of certain parameter values in SVM leads to diminished efficacy in effectively handling intricate datasets.

TABLE X. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND KNN MODELS

		Predicted	
		O	**R**
Actual	O	13189	777
	R	1215	9896
	Total	14404	10673

TABLE XI. THE CONFUSION MATRIX WAS DERIVED FROM THE INTEGRATION OF SQUENZEENET AND DECISION TREE MODELS

		Predicted	
		O	**R**
Actual	O	12343	1623
	R	1902	9209
	Total	14245	10832

In relation to the evaluation of algorithm performance in this work, the confusion matrix is employed as a metric to assess and comprehend the efficacy of the used Machine Learning algorithm in classification. This matrix facilitates an in-depth evaluation of the algorithm's performance, providing a deeper understanding of the model's strengths and limitations within the scope of this study. The confusion matrices for each method are displayed in Tables IV to Table XI. The table consists of a total of two rows and two columns. The initial row in the primary column displays instances of true positives (TP). The classification model accurately predicts occurrences that truly belong to the positive class. It refers to the count of instances where the model accurately predicted a good outcome and the actual result likewise turned out to be positive. The cell located at the intersection of the first row and the second column is referred to as false negative (FN). The model erroneously classifies occurrences that should belong to the positive class as negative. Put simply, it refers to the instances in which the model incorrectly predicted a negative outcome while the actual result was positive. The element located in the second row of the first column is classified as false positives (FP). The model erroneously classifies occurrences that should belong to the negative class as positive. It refers to the count of instances where the model made a positive prediction despite the actual outcome being negative. The cell located in the second row and second column represents the number of true negatives (TN). The categorization model accurately predicts occurrences that truly pertain to the negative class. It refers to the count of instances where the model made a negative prediction and the actual result was likewise negative.

The XGBoost and CatBoost classifiers demonstrated superior performance in accurately categorizing both organic and recyclable categories, with misclassified instances numbering less than 1000. The K-nearest neighbors (KNN) technique is considered to be one of the top three algorithms in machine learning. However, it has been shown that when used to certain datasets, especially those including recyclable classes, a significant number of misclassifications occur, with the misclassified instances exceeding 1000 in number. The data shown in Table VIII relates to the misclassification of the recyclable class in SVM specifically in cases where the achieved results exceeded 6000 data points. This numerical value exceeds the amount of accurately identified data.

IV. CONCLUSION

This study proposes a comprehensive analysis of the significant consequences of uncontrolled garbage accumulation in initiating fires that have adverse effects on both the natural environment and human society. A unique solution has been developed to address this issue, employing Machine Learning techniques to autonomously segregate garbage through the utilization of a highly efficient algorithm. The findings from the experimental analysis demonstrated that the utilization of SqueezeNet as an image recognition technique, coupled with XGBoost as the final classifier, emerges as the most optimal selection in the investigation, exhibiting exceptional performance.

This study also examined the effectiveness of SqueezeNet as a feature extractor in conjunction with a final classifier that differs from XGBoost. Various machine learning methods, including Random Forest, Support Vector Machine (SVM), Naïve Bayes, K-Nearest Neighbor (KNN), and Decision Tree, are commonly employed in the field of machine learning. The K-Nearest Neighbors (KNN) algorithm has exceptional performance, with a score exceeding 0.9 for all evaluation metrics. The lightweight convolutional neural network design of SqueezeNet enabled it to extract features that possess higher levels of informativeness and relevance in comparison to alternative models. Ensemble models such as LightGBM, XGBoost, and CatBoost improved overall performance by aggregating predictions from a restricted collection of fundamental models, which are typically shown as decision trees. Enhancing the system's ability to handle complex data may be achieved by the use of boosting techniques, such as error correction and prioritization of tough samples. The utilization of a confusion matrix was employed to assess the efficacy of a Machine Learning algorithm in the task of categorization. The classifiers XGBoost and CatBoost demonstrated exceptional performance in reliably classifying organic and recyclable categories, with a minimal number of misclassified examples, namely less than 1000. The K-nearest neighbors (KNN) approach, which is widely recognized as one of the leading algorithms, has been found to exhibit notable misclassifications in some datasets, notably in relation to recyclable classes.

The primary advantage of this research has great significance in addressing the issue of waste management. The use of automated trash segregation via Machine Learning techniques has the potential to mitigate the occurrence of fires, hence safeguarding ecosystems and infrastructure from detrimental impacts. Furthermore, the implementation of automated waste segregation has the potential to enhance operational effectiveness and safety within waste management systems, mitigate the likelihood of contamination, and contribute to the promotion of sustainable waste management practices. In addition, the utilization of this technology has the potential to mitigate the potential harm caused by human contact with dangerous compounds and foster ecological hygiene. Therefore, this research study significantly contributes to the preservation of the environment, mitigation of fire hazards, and enhancement of the community's quality of life. The utilization of Machine Learning technology, namely through the utilization of SqueezeNet and XGBoost, holds significant potential in the realm of automated waste segregation. This approach represents a crucial stride towards effectively tackling pressing waste-related issues and fostering sustainable advantages for both the society and environment.

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