Smart Waste Management: Object Classification for Recycling Optimization using Computer Vision and Deep Learning

MSc Research Project
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Abstract

In today's world, the waste generation is increasing exponentially, due to several factors like the surgical waste in COVID-19 pandemic, online shopping and packages, and population growth. There are different ways to mitigate and manage waste like circular economy initiatives, technological solutions, and policies and regulations. The main aim of this research is to develop a state-of-the-art waste classification system for waste management. The traditional methods for classifying waste depend on CNN (Convolutional Neural Networks), CNN models can differentiate the waste, but when similar waste types are present, it will be difficult to predict the type of waste and handle complex patterns for various waste streams. To address these limitations present in the current methodology, a novel framework integrates the benefits of different machine learning models like Convolutional Neural Networks and RNNs (Recurrent Neural Networks), these models specifically use LSTM (Long Short-Term Memory) networks for identifying complex patterns and temporal dependencies and a ResNet50-based CNN for extracting features from the dataset. In the individual models accuracy will be low compared to hybrid models, as hybrid models utilize the benefits from different machine learning models to enhance the predicting accuracy of the model. An extensive dataset is used for training the model, and the Adamax algorithm is utilized to improve the performance, the model is evaluated with several metrics and acquires an accuracy of 89.45%, this model has shown great performance in ROC analysis, recall, precision, and F1-score. With the assistance of this approach, there is a great chance to provide scalable and precise solutions for sorting waste automatically, and finally navigating towards more reliable waste management practices.

1 Introduction

Globally waste generation has increased to an extreme level and the traditional models suffer to manage the waste. There are various reasons for the rise in waste generation such as the expansion of different industries and urbanization. The waste generated in recent days has completely overwhelmed classical waste management systems, which leads to uncertainties in the degradation process and recycling. To address these limitations there is a great need for a technology-driven solution for enhancing the waste management system(Ahmed et al.; 2023; Choi et al.; 2023). As waste generation increases exponentially, there is a need for a smart waste management system and artificial intelligence has shown promising results in various fields, in this research we are exploring the benefits of AI (artificial intelligence) for efficiently handling the waste management process. Advanced deep-learning methods like object classification have been exceptional in automating and improving materials recycling (Yeaminul Islam and Alam; 2023; Mohammed et al.; 2023). By leveraging deep learning and artificial intelligence, the traditional models are enhanced in terms of sorting the waste, more often they are prone to error, labor-intensive, and fail to handle growing waste materials.

Deep learning is a part of machine learning, It uses neural networks that automatically learn and extract features from datasets, they are mostly used in the field of image processing and NLP (natural language processing), in this study we are leveraging CNN (Convolutional Neural Networks) in waste management to identify and classify images to recognize the various types of waste materials like glass, metals, and plastics. However, waste management is not simple work, mostly depends on identifying the dependencies and complex patterns within the data, where CNN capabilities alone are not enough Rad et al. (2021); Ren et al. (2019). There are challenges if only the CNN model is used for waste management, to overcome these challenges, a hybrid model is developed to combine the strengths of two different models and enhance the predicting capability in waste management.

The models are CNN and RNN, where CNNs capture spatial features from images and RNNs are good at identifying temporal dependencies within the data. In a hybrid model, the feature extraction and sequence modeling strengths are gained to develop a more dynamic waste classification system. CNNs and RNNs integration is a smart option for waste management systems, as it leverages the different approaches in the dataset. A hybrid system can capture temporal dependencies and complex patterns within the dataset, and the classification is better in comparison to CNN models alone, the overall accuracy has increased gradually. Additionally, this hybrid model can dynamically adjust to environmental conditions as well as differences in waste materials, these properties make them well-suited for real-world problems. The enhancements made by the hybrid model in capturing complex patterns and temporal dependencies work efficiently with the goals of smart cities and enhance waste management systems. The hybrid CNN-RNN models have shown promising results in terms of waste management systems, but they possess a few limitations such as requiring a large dataset to train the model and integrating the hybrid model into the current systems, as they require more computations for training the hybrid model. These significant challenges need a multidisciplinary approach, integrating expertise in waste management, environmental science, and AI.

This research aim is to explore the hybrid model by designing, implementing, and evaluating for classifying objects in waste management systems. Once the design phase of the model is completed and the model is implemented in real-world scenarios, will help in finding the accuracy of the model, and assist in finding the areas where enhancement is needed. The goal is to provide optimization of recycling processes and enhancements in the waste management systems. With this research, we contribute towards a more sustainable and reliable waste management system in this rapidly evolving world.

1.1 Motivation

There are several important factors, which motivate this research. First, the rapid growth in urbanization can lead to multiplying global waste by 2050, approximately it will reach a forecasted value of 3.4 billion tonnes, which shows a promising area for enhancement in waste management systems (Kaza et al.; 2018). Second, rapid urbanization and online shopping lead to a large amount of waste generation, and not aware of proper disposal of waste, so the improper disposal of waste creates environmental degradation. For example, when the waste is disposed of in a particular area, that landfill releases significant amounts of methane and greenhouse gases which can noticeably lead to climate change (Bogner et al.; 2008). Further, recyclable materials are not managed properly, often resulting in the depletion of natural resources and demands for new raw materials (Geyer et al.; 2017). Third, manual waste sorting poses remarkable health risks and compared to automated sorting waste, human sorting is inefficient and workers are exposed to unsanitary conditions (Bournay et al.; 2017). When compared to manual sorting, automated sorting can leverage advanced technologies like deep learning and computer vision for sorting, this will reduce the health risks of workers and enhance the efficacy of recycling operations. To overcome from these types of significant challenges, there is a great requirement for a smart waste classification system that has the potentional ability of mitigating misclassification, improving the recycling efficacy, tackling the contamination rates, and allowing it as a more reliable waste management practices. This research contributes to reduce the greenhouse gases and better conservation of sustainability of resources (Rad et al.; 2021).

1.2 Research Objectives

This research aim is to observe the challenges faced by the traditional types of methods, manual classification of waste, and misclassification of the recyclable waste and use more sophisticated deep learning models with the assistance of the computer vision approach methodology. The key objectives are:

- To Develop and implement Deep Learning-Based Waste Classification System: Implementing the hybrid model of CNN and LSTM components assists in classifying the waste materials into various categories like metal, recyclable, and organic.
- To Enhance Model Performance By Data Processing Techniques: For improving the model's performance, data preprocessing and augmentation methods are assigned to enhance the accuracy of the classification model.
- To Assess the Effectiveness of the Proposed Model: Different evaluation metrics are used to evaluate the model's performance in real-time scenarios.
- To Offer Insights into Model Installation: It is important to analyze the practical implications of installing the hybrid model in real-world scenarios, including the cost and efficacy.

1.3 Research Questions

It is important to know the influence of deploying a model into real-world scenarios before developing the model. How has the classification accuracy increased in recycling systems by integrating computer vision and deep learning technologies? This question discovers the advantages of advanced deep learning and machine learning models to enhance the sustainability of sorting waste in rapid urbanization globally.

- How does the proposed hybrid model that integrates CNN and LSTM work better than the traditional waste classification models based on accuracy and reliability? This question compares the benefits of traditional models or manual sorting models over completely automated models.
- How do the data preprocessing techniques influence the performance of waste management systems? This question concentrates on different preprocessing method's influence on the reliability, robustness, and efficiency of the model.
- What are the challenges and advantages related to the deployment of a hybrid model in real-world recycling facilities? This question evaluates the feasibility of integrating a hybrid model into real-world scenarios and includes their economic impact.

Advanced machine learning and deep learning models have shown great results in various domains, and now they are being explored to get more accuracy for classifying waste, this study's questions and objectives aim to develop a smart waste classification model, to enhance the classification of waste, advance recycling systems and notice the challenges of significantly growing waste.

There is a great need for a novel hybrid framework, the hybrid models integrate multiple machine learning models and leverage its advantages for capturing the spatial data in images, identifying the temporal dependencies present within the sequential data. In this hybrid approach, CNN-RNN and LSTM models are developed and implemented on a large dataset to show enhanced accuracy in classifying waste mitigating the misclassification of recyclable waste, and organic waste. The outcomes of this research highlight the enhancements in promoting environmental sustainability and reducing classification errors in waste management systems.

2 Related Work

2.1 Overview of Waste Management and Recycling

For several years waste generation has been increased and it is an important area to find enhancements for waste management, it is influencing the environment as well as human health. There is a great need to integrate advanced technology for segregating waste, traditional models used only the CNN model for capturing the spatial features present in the images, these images are captured with the assistance of computer vision, the CNN model has revolutionized the field of waste management. Now advanced deep learning model uses neural networks to advance waste management systems, sorting of waste, and recycling enhanced to encourage product recycling rather than demanding new raw products. With the enhancements in the technology and integration of multiple models, the waste management system is automated, offering sustainable and reliable enhancements in circular economy(Geyer et al.; 2017). These advanced models have shown remarkable results in waste management, but there are significant challenges in accurately sorting waste, this is the main challenge because sorting is mainly dependent on manual sorting and automated sorting has significant errors (Silva et al.; 2020).

2.2 Challenges in Waste Sorting

There are different types of waste such as plastic, metal, and medical waste. manual sorting is time-consuming and also workers are exposed to dangerous environments leads to health issues (Gupta; 2019). Waste sorting manually leads to inefficiencies and contamination, it will increase the cost of processing the recycled materials and the contamination will reduce the quality of the product (Bournay et al.; 2017). To surpass the challenges automated sorting system is developed with enhancements in sensor and robotic technologies and uses a computer vision technology for efficiently sorting the waste. But the traditional automation faces challenges with a variety of waste material types and complicated waste streams, there is a great research opportunity to enhance in this area (Rad et al.; 2021).

2.3 Computer Vision and Deep Learning appraoches

Computer vision and deep learning can be used to overcome these challenges in waste sorting. CNNs have been very successful in image recognition, and as such are suitable for the classification of waste materials based on features such as colour and shape. The literature has revealed that CNNs can effectively recognize and classify various forms of waste including plastics, metals, and organic substances (Ren et al.; 2019). For improving the generality and effectiveness of sorting, Recurrent Neural Networks (RNNs), which on its own contains LSTM layer, are able to analyze sequential data and temporal dependencies, are effective for fast-moving conveyor belts and un-stopped waste flows (Hochreiter and Schmidhuber; 1997).

Artificial intelligence is known for capturing complex patterns and classifying objects, these advantages are needed for surpassing the limitations faced by traditional models. CNNs have shown exceptional results in identifying spatial features in images, by leveraging these models, it will be easy to detect and classify the waste materials relying on images (Krizhevsky et al.; 2012). In different studies, it is proven that CNN can classify objects accurately, and it has exceptionally performed in waste management by differentiating between types of waste like metal and plastic (Ren et al.; 2019). By utilizing AI and CNN waste management systems can detect and classify waste depending on the visual cues, but these models lack in recognizing temporal dependencies, to surpass this, the existing models are integrated with RNNs and LSTM networks. This integration will give an additional advantage for sorting the waste (Hochreiter and Schmidhuber; 1997).

2.4 Implementation of CNN-RNN Architectures

A hybrid model of CNN-RNN has been implemented in various domains which includes sequential data and has shown significant results, This methodology is implemented for classifying the waste materials and has shown enhanced results in classification (Donahue et al.; 2015; Rajagopal et al.; 2024). A hybrid model of CNN-RNN is utilized, where the convolution neural network (CNNs) recognizes the spatial characteristics features from the images and RNNs types of model are good at recognizing the temporal dependencies within the complex data. In a hybrid model, the feature extraction and the sequence modeling strengths are gained to construct a more powerful and dynamic waste classification system (Ren et al.; 2019; Lilhore et al.; 2024). This approach methodology has demonstrated the outstanding results of extensive & complex datasets by accurately recognizng the materials and a hybrid model can be deployed on real-world scenarios.

Research on the automated type of classifying waste material in a recycling facility has demonstrated its outstanding results while comparing it to manual type of sorting the waste and this automated type of sorting is less time-consuming and has saved the operational costs (Silva et al.; 2020). Various studies have highlighted a hybrid model's accuracy is superior high while comparing it to the individual models, here to improve the effectiveness of sorting waste material. For example, the deep learning model is utilized by the RecycleNet system to mitigate the misplacement of recyclable materials (Rad et al.; 2021). In Real-world applications outline the advanced deep learning models for the efficiently improving the sorting of waste materials.

2.5 Environmental and Economic Benefits

Assimilating the Revolutionised & advanced deep learning and machine learning models with the process of automated sorting and classification of the waste materials offers the various advantages. Where by improve the accuracy of sorting, we can decrease the manual power for sorting and reduce the health risks, the recyclable materials can be recognizable and separated efficiently without the pollutant, which will handle the demand for the raw materials and towards the production of raw materials (Geyer et al.; 2017). In aspects of the economic terms, operational effectiveness has been improved by the recognizing and efficiently sorting the waste materials, leads to decreases the labor costs and health risks. These chracterstics attributes offers a great opportunity for improving the waste management approach technologies (Kaza et al.; 2018).

2.6 Future Directions and Challenges

The assimilation of the advanced deep learning algorithm and computer vision techniques has demonstrated the remarkable results, but their significant challenges to assure the scalability of the model architecture and effectiveness in different different types of waste environments continued. Moreover, the data security and privacy have to be observed in the public waste systems (Gupta; 2019). Additionally, the current models can be incorporated with the technologies of IOT (Internet of Things) and edge computing to improve the accurate sorting & classification of waste materials, and the models must be dynamically persist to work in several types of environmental conditions (Rad et al.; 2021).

Despite these opportunities, there are challenges involved in the integration of computer vision and deep learning in waste management. It is important to make these kinds of systems more reliable and adaptable in various and changing waste conditions. However, the data privacy and security issue especially on public waste management systems must also be solved to enable the uptake of the system by the public (Gupta; 2019). Further studies should aim at working on more complex models which can be applied for more various types and conditions of waste and in addition there also should be done studies

Figure 1: Various distributions of image sizes in the dataset

for applying other future technologies like IoT and edge computing for the improvement of the system performance and sustainability (Rad et al.; 2021).

In conclusion, the literature emphasizes the need for using computer vision and deep learning in waste management for change. Thus, they have the potential to overcome existing difficulties related to the manual sorting as well as enhance the efficiency of the processes of recycling. Such an approach is essential to extend the environmental and economic benefits accruing from development and investment in this field as the world strives to achieve sustainable goals. Overall, this section outlines the importance of machine learning and deep learning models impact on waste management systems. With the integration of these technologies, automation is achieved, manual errors are mitigated, and reduced the misplacement of recyclable materials. Continuous innovation is required to explore various algorithms to enhance waste classification models and navigate toward sustainable and robust models.

3 Methodology

The waste generation has increased exponentially because of various factors, this research's main objective is to enhance the waste management system, and to accomplish this objective, a novel smart waste management system is required. In this methodology, we develop a smart waste classification system that leverages advanced deep learning techniques and accurately sorts the waste based on its type. In this section, the developed model's methodology is explained from the designing phase to the evaluation phase, and each phase is explained systematically and includes collecting data, preprocessing, training, and testing the model additionally performance metrics used for evaluating the performance of the model.

3.1 Data Collection

The basic step for training the model is collecting the dataset, and the dataset comprises various datasets of waste images, the images denote different categories of wastes like recyclable, glass, metal, and organic wastes. the dataset is collected from publicly available images for real-world scenarios and the dataset is added with additional images taken in different environments, to check the efficiency of the model for accurately sorting the waste materials. Once the dataset is collected successfully with types of waste images, the further step is data preprocessing. The dataset will be splitted for testing and training with a split of 80% for training and 10% each for testing and validation.

3.2 Data Preprocessing

Data reprocessing is done before splitting the data for training and testing to guarantee the quality and consistency of the dataset (Hurtik et al.; 2019). All the images collected are 224x224 pixels in size, to reduce the computations for reducing the images to the same size and normalizing to the range of [0,1], this process will help the model without spending more computations on normalizing the dataset and concentrating on faster training of the model. Further, brightness adjustments, flipping, rotation, and zooming of the images come under the data augmentation models, this enhances the model's performance on real-time data. This step is important to guarantee the quality of the dataset, and the dataset is split into training and testing, where 80% of the dataset is used for training the model and the remaining 20% is used for testing the model.

3.3 Model Development

The proposed system CNN-LSTM Hybrid model for classification of waste images based on both spatial and temporal characteristics of the images (Ren et al.; 2019). In terms of model architecture, it aims to achieve the highest accuracy rate by employing several sophisticated methods.

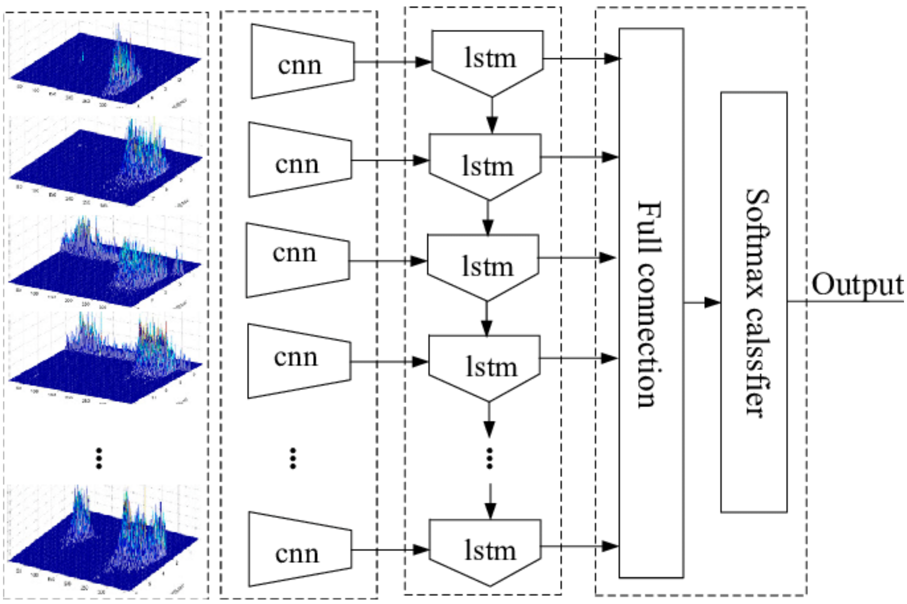

Figure 2: CNN-LSTM Hybrid Architecture (Rad et al.; 2021)

The CNN component will use the ResNet50 model because the model is able to extract feature hierarchies from images. CNN based model ResNet50 will be used to extract features from the images and the final few layers of ResNet50 network will be updated or trained for the purpose of waste classification. The output from the CNN componet will then be transported to an RNN, precisely LSTM model which is aimed to identify temporal dependencies in the sequence of feature vectors extracted by ResNet50 model. This configuration is useful in understanding dynamic changes and enhancing the identification of categorical changes in situations which requires constant movement like moving conveyor belts and constant waste flow (Rajagopal et al.; 2024). After the LSTM layer, there will be other dense layer to make further processing of the feature extraction and the actual classification will be done. We used L2 regularization which will be applied to avoid over-fitting (Lilhore et al.; 2024).

3.4 Model Evaluation

The cross-section validation and testing data set will be used to evaluate various performance metrics of the trained model. A classifier for waste images will be developed, it will measure the ability of the algorithm in classifying images correctly and the overall accuracy will be determined. A confusion matrix will aid in the identification of misclassification patterns in performance by examining result in categories. In order to get a more detailed evaluation, specially in cases of handling imbalanced classes, precision, recall and F1-score will be calculated. Finally, the performance of the model on classifying the classes will be assessed using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC). These measures will all together help in evaluating the effectiveness of this model and also identifying the areas where it requires enhancement.

3.5 Summary

This research methodology highlights the extensive approach to developing a hybrid model for a smart waste classification system. The model model comprises advanced deep learning and computer vision, this hybrid model is used to take advantage of deep learning and computer vision to enhance recycling management and sustainable waste sorting systems. The comprehensive approach for data collection assists in robust and scalable evaluation measures and guarantees to notice the challenges in the current waste management models.

4 Implementation

There are several key factors for implementing waste management systems, all the key attributes are combined as a symmetrical structure. The architecture for implementing waste management consists of various steps: collecting data, preprocessing, training, and testing the model additionally performance metrics are used for evaluating the model's performance. This model needs software and hardware components to deploy in real-time scenarios and sort the waste materials efficiently. Hardware components, need a high-resolution camera to identify the images of waste materials and an automated mechanical system for sorting the waste. Software components need an advanced deep-learning model to install on a powerful server.

4.1 Hybrid CNN-RNN Model Development

The hybrid model is developed to combine the strengths of two different models and enhance the predicting capability in waste management. The models are CNN and RNN, where CNNs capture spatial features from images and RNNs are good at identifying temporal dependencies within the data. This integrated approach will be the optimal solution for sorting the waste materials and real-world scenarios, the waste material will be moving on a conveyor belt and these models will capture the images and classify the wastes accurately.

4.2 CNN Component: Pre-trained ResNet50

The Convolutional Neural Network (CNN) component of the model is built upon the ResNet50 architecture, a highly regarded deep learning model that has demonstrated exceptional performance in image classification tasks. ResNet50, subset of the Residual Network family, is known for its deep architecture, involving of 50 different layers that allows it to learn complex and hierarchical characteristics of features from the images. The key innovation of ResNet50 lies in its use of the residual nature of connections, which enables the model architecture to handle the problem of reducing the gradients and facilitate the training of very deep networks.

The pre-trained ResNet50 model utilizes the 50 layers that allows them to recognize and learn the intricate patterns in the data, and they have represented the outstanding results in feature extraction from the different different images. By using the advantages of transfer learning of pre-trained models, the model can remember the important features in the dataset. With the assistance of transfer learning ResNet50 can identify the visual features, that are useful in future predictions.

ResNet50 has a unique feature that can be modified depending on the problem, in this case, the last few layers of ResNet50 are tailored by adjusting the weights and this will assist in dynamically identifying unique and minute features present in the images which can significantly enhance the sorting capabilities of the model. Fine-tuning the model to distinguish different types of waste materials such as glass, metal, recyclable, and organic.

4.3 RNN Component: LSTM Layer

The CNNs capture spatial features from images, the output is in he form of feature vectors, this is given as input to RNN (Recurrent Neural Network), where it captures the sequential data dependencies. LSTM (Specifically, a Long Short-Term Memory) model is used in sequential datasets for capturing the temporal dependencies, in this research ResNet50 generates the sequence of feature vectors and LSTM is used to identify the temporal dependencies in the sequence. LSTM is a part of RNN models, but they have shown excellent results in capturing long-term dependencies in the data, LSTM networks can remember the important dependencies in the dataset and discard the unnecessary information. This particular feature makes it suitable for enhancing the sorting of waste materials.

LSTM layer plays a significant role in identifying the feature dependencies in various fields, in real-world scenarios of sorting waste materials LSTM plays a main role in extracting features. when they waste materials are moving on a conveyor belt and pass through the view of a high-resolution camera, the LSTM model processes the sequence of waste materials and extracts the feature, this will help in the future when processing the same features, it will easily detect the type of material and this process will give additional information to the waste management system and improves it classification.

The hybrid model combines the important features from both models, where the CNN model identifies the spatial features and the LSTM model captures the temporal dependency in long sequences. This model has integrated two most useful techniques for efficiently sorting the waste materials but also enhanced the acknowledgment of materials over time for more accurate and enhanced sorting results.

4.4 Additional Dense Layers and Regularization

An additional fully connected dense layer is integrated into the LSTM model that processes the features extracted from the LSTM model. Integrating dense layers provides an additional opportunity to refine the features generated by CNN-RNN components. Finally, this leads to the sorting of waste materials, The main aim of dense layers is to combine the features coherently to make the final decision of sorting the waste materials into a particular category.

To prevent overfitting, which is a common issue in deep learning models, L2 regularization is applied to the dense layers. Overfitting occurs when a model becomes too specialized in the training data, resulting in poor generalization to new, unseen data. L2 regularization addresses this by adding a penalty term to the loss function, which discourages the model from assigning excessive importance to any single feature or connection. This penalty helps to ensure that the model remains robust and capable of generalizing well to different waste classification scenarios.

```
base_model = ResNet50(include_top=False, weights='imagenet', input_shape=input_shape, pooling='max')
# Freeze ResNet50 layers
for layer in base_model.layers:
    layer.trainable = False
# Add layers on top of ResNet50
x = base_model.output
x = BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001)(x)
# Flatten the output of ResNet50
x = Flatten()(x)
# Reshape for LSTM input
x = Reshape((-1, x.shape[1]))(x)
# LSTM layer to capture temporal dependencies
x = LSTM(128)(x)
# Additional dense layers with regularization and dropout
x = Dense(256, kernel_regularizer=regularizers.l2(l=0.016),
          activity_regularizer=regularizers.l1(0.006),
          bias_regularizer=regularizers.l1(0.006),
          activation='relu')(x)
x = Dropout(rate=0.4, seed=75)(x)
# Output layer
predictions = Dense(num_class, activation='softmax')(x)
# Create model
model = Model(inputs=base_model.input, outputs=predictions)
```

Figure 3: Code Implementation of Hybrid model

4.5 Model Training

To guarantee the optimal performance of the model, it is trained with a subset of the dataset along with certain configurations. To increase the efficacy and robustness Adamax optimizer is used, for handling different class sorting problems, and categorical cross-entropy loss is assigned. To enhance the model performance, it is important to balance memory and the training batch size, in this case, the batch size is considered as 16, utilized early stopping and 50 epochs.

A structured approach is important for automation in waste classification and it involves several steps like collecting the dataset, cleaning and preprocessing, training and testing the model, and calculating the model performance depending on the evaluation metrics. A hybrid model is used to enhance the performance of sorting, and classifying different waste materials like metal, recyclable, glass, and organic waste. This model can be implemented successfully for real-world scenarios because of its extensive training dataset and it contributes towards sustainable and reliable waste management practices.

5 Evaluation

An extensive assessment is involved in evaluating the performance of the smart waste classification system, in this section extensive details of the results of evaluation parameters like confusion matrix, ROC (Receiver Operating Characteristic) curve, and classification metrics, these parameters also include the training and testing performance. The outcomes highlight the effectiveness and sustainability of the proposed model and recognize the areas for future enhancements.

Dataset	Loss	Accuracy
Training	0.0352	0.9961
Validation	0.4919	0.8555
Testing	0.3827	0.8945

Figure 4: Performance of Model Accuracies

5.1 Training and Validation Performance

In the training process, 10 epochs are considered, and there is a significant enhancement in the prediction of the model's performance eventually. The accuracy obtained in the first epoch is 91.35% and the loss value is 0.5302. By the time the tenth epoch is reached the accuracy has remarkably increased accuracy and the mitigated loss value, values of accuracy and loss are 99.69% and 0.0418 respectively.

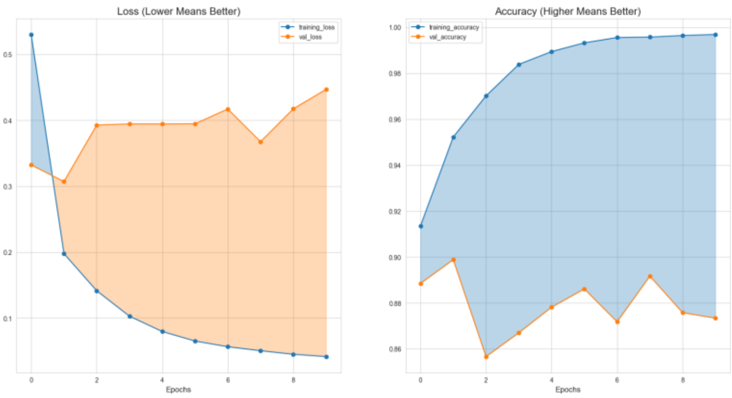

Figure 5: Model Performance while Training

We have seen the overall performance of the model and its enhancements in the classification of waste materials. This validation set has offered the model's performance assessment for individual epochs, the accuracy of the model has not evolved continuously, and there are fluctuations throughout the validating face. For instance, the accuracy obtained initially is 88.85% and the loss value is 0.3324. the highest accuracy was achieved at the eighth epoch which is 89.17% and the loss of 0.3676. However, the model performance has increased gradually for identifying and classifying unseen data.

5.2 Performance Metrics

5.2.1 Classification Report:

Class	Precision	Recall	F1-Score	Support
O	0.83	0.98	0.90	703
R	0.97	0.75	0.84	554

Table 1: Performance Metrics for Different Classes

The results presented in Table 1 show the efficiency of using a hybrid model, in this research, only the recyclable materials (R) and organic waste (O) materials are classified. The hybrid CNN-LSTM model has performed accurately and acquired a precision of 0.83 for organic waste and the recall evaluation parameter value is 0.98 which is exceptionally high for classifying the organic waste. This indicates model has accurately classified organic waste and recyclable waste, only a negligible amount of organic waste is misclassified as recyclable material.

The balance between the model's precision and recall demonstrates the robustness of the model handling classes, the F1-Score of organic waste is 0.90. This exceptionally high value of F1-Score demonstrates that CNN and LSTM have performed exceptionally well in identifying the spatial features and temporal dependencies available in the data.

However, the hybrid model has shown different results for recyclable materials, the precision acquired is 0.97, this indicates that the model has exceptionally classified the recyclable materials from the conveyor belt, and recall value is relatively low compared to organic waste, here most of the recyclable waste materials are misclassified as organic waste. F1-Score indicates there is a great chance for enhancement of the model for further predictions in identifying recyclable waste materials.

5.2.2 Confusion Matrix:

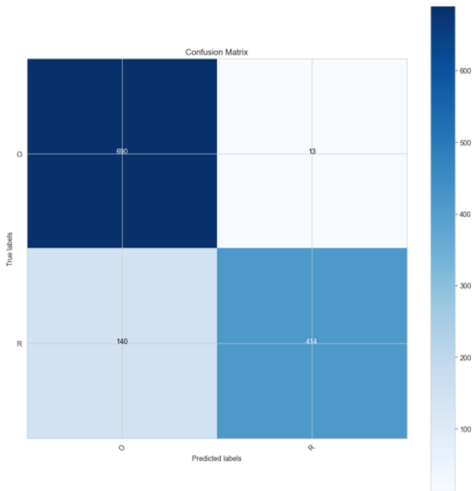

Figure 6: Confusion Matrix

The confusion matrix in Table 2 and Figure 6 offers a clear picture of how the hybrid mode by integrating CNN-LSTM is performing in sorting the organic waste (O) as well as the recyclable materials (R).

Table 2: Confusion Matrix

	Predicted O	**Predicted R**
Actual O	690	13
Actual R	140	414

The confusion matrix is used to demonstrate the actual true values and actual negative values of the waste classification system. A hybrid model has significantly recognized 690 images from actual 703 images of organic waste. The hybrid model combines the important features from both models, where the CNN model identifies the spatial features and the LSTM model captures the temporal dependency in long sequences. This model has integrated two most useful techniques for efficiently sorting the waste materials but also enhanced the knowledge of materials over time for more accurate and enhanced sorting results. The accuracy explains the robustness of the model, with only very few misclassifications (only 13 instances).

But, in the case of recyclable materials, the model struggles to differentiate from organic materials, there are 554 actual recyclable images present, and the model misclassified 140 materials as organic waste. This accuracy explains that the CNN model can not identify the delicate spatial features present in the dataset and the LSTM model fails to capture the dependencies in the sequential feature data generated by the CNN model.

It is evident from the confusion matrix, that few areas require special attention and fine-tuning the model to recognize recyclable data, to increase the efficiency of the model it is important to train the data efficiently or to add feature extraction techniques for sorting between the organic and recyclable data. This approach can reduce the confusion between the two classes and can enhance the classification performance.

5.2.3 ROC Curve and AUC

The ROC-AUC curve shown in Figure 7, is one of the evaluation parameters, and the area under the curve value is 0.86. This AUC curve value indicates that the model is efficiently distinguishing between the two classification classes. If the value of AUC indicates 1 then it is a better-performing model, the value we acquired is 0.86 and this suggests that the model is effectively balancing specificity and sensitivity.

The hybrid model combines the important features from both models, where the CNN model identifies the spatial features and the LSTM model captures the temporal dependency in long sequences. This model has integrated two most useful techniques for efficiently sorting the waste materials but also enhanced the knowledge of materials over time for more accurate and enhanced sorting results. Still, there is room for enhancements because the AUC curve is not perfect.

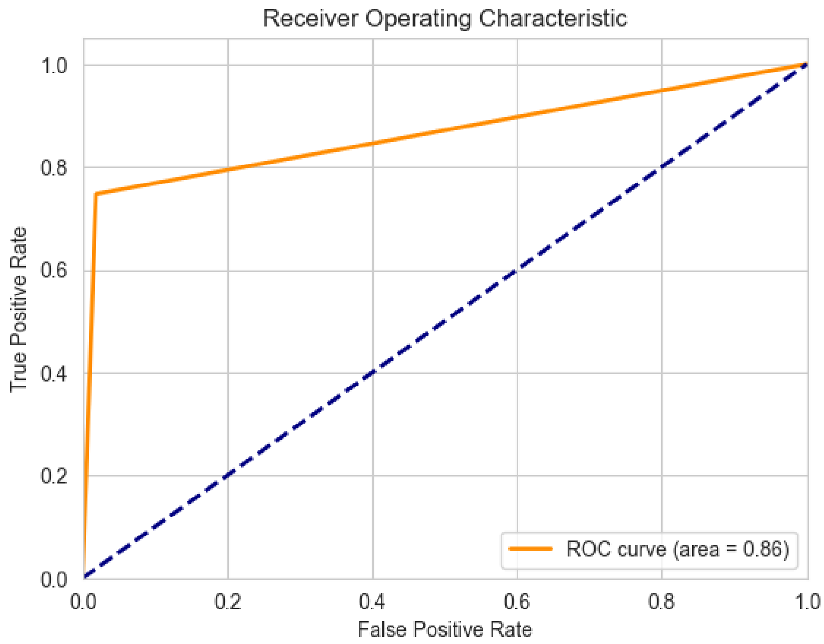

Figure 7: ROC and AUC Curve

5.3 Discussion

In this section, the discussion is about the development, testing, and results of smart waste classification systems. Evaluating the hyperparameters, performance metrics, and the results of the testing, will give the highlights of the model's performance and also the scope for future enhancements.

5.3.1 Hyperparameters and Their Impact

In this research, hyperparameters are fine-tuned and carefully selected to enhance the model's accuracy and improve the identifying and sorting capabilities.

- Optimizer: The Adamax optimizer is known for efficiently handling complex patterns in large datasets. It integrates the advancements of the infinity norm and the adaptive learning rates, which will gradually enhance the model performance
- One of the main features is choosing the perfect learning rate in this case it is 0.001, this will create a balance without overfitting the model
- For training the model batch size of 16 is selected for 50 epochs, to balance between the memory utilization and training speed of the model, this will allow the model to efficiently classify the classes, without increasing the computational power.
- A hybrid model of CNN and LSTM is trained with 10 epochs until the model is properly combined.
- We also utilize L2 regularization to avoid overfitting the model and used a dropout rate of 0.4

- Activation Functions: A softmax activation function is the final layer of hyperparameters, this activation function generates the class probabilities, this option is best for multi-class sorting tasks, by guaranteeing the efficiency in model results.

5.3.2 Interpretation of Training and Validation Performance

In the training process, 10 epochs are considered, and there is a significant enhancement in the prediction of the model's performance eventually. The accuracy obtained in the first epoch is 91.35% and the loss value is 0.5302. By the time the tenth epoch is reached the accuracy has remarkably increased accuracy and the mitigated loss value, values of accuracy and loss are 99.69% and 0.0418 respectively. This significant enhancement validates that the model has learned the features and temporal dependencies of the waste images. In validation performance, the accuracy obtained initially is 88.85% and the loss value is 0.3324. the highest accuracy was achieved at the eighth epoch which is 89.17% and the loss of 0.3676. However, the model performance has increased gradually for identifying and classifying unseen data.

5.3.3 Analysis of Testing Performance

The model's accuracy after testing is 89.45% this explains the model's robustness and dynamic ability to capture the new and unseen data. The obtained high accuracy demonstrates that the hybrid model is capable of working on real-time data, it can classify between recyclable and organic waste materials. The testing loss value is 0.3827 explains the model's efficiency in classifying the waste data.

Figure 8: Actual and Predicted Samples through Model

5.3.4 Potential Areas for Improvement

The hybrid model has shown some exceptional results in classifying the organic and recyclable waste materials, there is a need for refinement in several areas:

- Handling Misclassifications: The recyclable waste is misclassified as organic waste, to overcome this fine-tuning of the model is required, training with the extensive dataset, and assigning feature extraction strategies to the currently existing models.

- Class Imbalance: Models recall value for recyclable data can be enhanced by distributing the classes equally. Approaches like sampling with weights, over-sampling, and under-sampling can be used to reduce this issue.
- Incorporation of Multimodal Data: Combining extra data modalities including audio signals and infrared imaging will offer a better dataset to train the model. Integrating visual information with multiple sources of information will increase the efficiency of the model's performance for accurately distinguishing between recyclable and organic waste materials, otherwise, it will be difficult to sort only based on visual data.
- Exploration of Alternative RNN Architectures: LSTM models are known for capturing temporal dependencies in the dataset, and they have shown significant results in classifying waste materials. Other RNN models can be used to explore their efficiencies for classifying waste materials.
- Implementation of Real-Time Processing Capabilities: Supporting the model to work on real-time datasets like efficiently classifying the waste materials when they are moving on the conveyor belt. This will highlight the challenges faced by the models for efficiently classifying the waste materials. This will provide a great opportunity for the models to notice the areas of enhancements.

Evaluating the training, testing, and performance metrics demonstrates the model's sustainability and capacity to classify unseen data. The results of the hybrid CNN-LSTM models have shown significant enhancements, but few areas require further enhancements to increase the model's sorting accuracy. By integrating feature extraction tools we can further enhance the model's capabilities for sorting.

6 Conclusion

This research aim is to develop a novel framework for classifying waste management for sorting between recyclable and organic waste materials, this novel framework utilizes a hybrid model of advanced deep learning models and computer vision, and this model is designed to notice the limitations of existing models, manual waste sorting, prone to error, and health risks. By using the hybrid CNN-RNN model, the proposed model can capture spatial features from the images, and it has shown great accuracy and sustainability for sorting waste materials.

The extensive methodology of this research includes various sites for accurately classifying the waste materials, the steps involved in this research methodology are data collection, cleaning and preprocessing, development of the model, training, and testing, and evaluating the performance metrics. High-resolution cameras capture the images of waste materials and the collected data is preprocessed to remove duplicate images.
The pre-trained ResNet50 model uses 50 layers to capture the complex patterns and dependencies in the data, LSTM model is used to capture the temporal dependencies in the feature sequence generated by the RNN model, for enhancing the model's performance accuracy. There are several evaluation metrics to evaluate the model performance, some of the evaluation metrics are F1-Score, precision, recall, accuracy, and ROC AUC curve. The results obtained from the performance metrics demonstrate the model has

achieved great accuracy and enhancements in sorting the waste materials. It also showcased the model's capabilities to work on real-time applications of waste classification systems. However, there are significant challenges to address, where the model requires enhancements and integration of feature extraction techniques will improve the model's sorting techniques. The hybrid model has misclassified recyclable waste materials as organic waste materials, there is a scope for future enhancements in for accurately sorting the waste materials.

7 Future Work

This hybrid model has shown significant enhancements for classifying the waste materials, but several areas require further enhancements to improve the model's accuracy and expand its applications:

- Improving Classification Accuracy: Feature extraction techniques can be integrated into the existing models, to enhance the model's classification for waste materials. Different types of waste materials can be included in the current dataset to increase the dataset diversity, so the model training on this dataset will have more efficiency in classifying the waste materials.

- Addressing Class Imbalance: Techniques like utilizing class weights, oversampling, and undersampling during the training phase will automatically reduce the class imbalance. this will increase the recall value of the model.

- Real-Time Performance Optimization: The existing models exhibit great accuracy and scalability, it is important to exhibit the same results on real-time applications. Future work can concentrate on mitigating the computational requirements and deploying them on real-world waste management applications.

- Environmental and Economic Impact Analysis: It is important to conduct an extensive analysis of how the automated model is influencing the environment and what are the advantages of this model, developing a more enhanced model that mitigates methane emission and greenhouse gases, operational cost savings and can assist in conserving the resources.

In conclusion, this study exhibits the advantages of utilizing deep learning and computer vision technologies for smart waste classification. The hybrid model of CNN-LSTM provides an efficient solution for sorting waste material automatically and provides a reliable waste management system. The future scope will concentrate on fine-tuning the models, integrating feature extraction techniques, and exploring new directions to enhance the model's applications in real-world scenarios, assisting the models towards global sustainability.

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