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Improving multi-material categorization accuracy in automated waste management using convolutional neural network

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ABSTRACT

The pervasive issue of waste management requires a comprehensive examination of waste classification, dividing it into organic, inorganic, and residual categories. This research employs a convolutional neural network (CNN) as the principal model, utilizing a dataset of 1,049 hand-annotated images taken under diverse lighting conditions and angles to replicate real-world environments. A thorough data augmentation process helps balance the classes and improve the overall quality of the data. The CNN design consists of three convolutional layers, succeeded by flattening, pooling, and dense layers. It utilizes ridge (L2) regularization and dropout to reduce overfitting. The Adam optimizer was used to train the model for 50 epochs. The research showed an accuracy of 87% overall, with inorganic waste classification reaching the highest precision of 0.96. Sorting organic waste remains difficult due to fewer training samples and greater variability. Meanwhile, having good lighting and the right viewing angle helps improve both the ease and accuracy of the sorting process. While CNNs show great promise for improving complex waste sorting systems, more work is needed to reach their full potential. The proposed approach supports building efficient and eco-friendly automated waste management systems, promoting sustainable urban waste solutions.

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1. INTRODUCTION

One of the most difficult things modern cities face today is waste. The amount of waste generated is becoming a major problem, along with the growth of the population and human consumption of various types of food. If no major action is taken, the amount of waste generated worldwide is projected to increase from 2.01 billion tons in 2016 to 3.40 billion tons by 2050 [1], [2]. The Ministry of Environment and Forestry stated that Indonesia itself generates over 175,000 tons of waste per day, or 64 million tons annually. Artificial intelligence (AI) is a technology that can help us overcome this problem by changing the way handle waste. This gives us a new way to handle the difficult work of collecting, sorting, and recycling, and to understand how types of waste can change due to light, temperature, and humidity [3], [4]. There is research that found that using AI to manage waste can save up to 20% in costs and speed up procedures by up to 30%. AI can find patterns, recognize trends, and give us new ideas that can revolutionize the way think

about and handle waste. For example, this can help us sort waste better, estimate how much heavy metal is in compost, and simulate how waste is burned [5].

The use of AI in waste management has shown promising potential in many areas. Researchers have proven that AI systems with computer vision can sort waste with up to 95% accuracy in detecting and separating various forms of waste [6], [7]. This technology has proven to make the recycling process much more efficient. Researchers have concluded that AI can help make waste collection routes more efficient. A comprehensive study shows that using AI algorithms to plan routes can save up to 25% on fuel and cut waste collection time by up to 30% [8]–[10]. This helps the economy and reduces carbon emissions. Some studies have examined AI models to estimate how much solid waste will be generated in cities [11], [12]. These models have been able to predict the amount of waste with an accuracy of 80% or more [13], [14].

However, there are several issues with using AI for waste management, such as data quality and availability, privacy concerns, and high upfront costs, which can range from $500,000 to millions for medium-scale systems [15]. Other problems include results that are not always reproducible, limited real-world applicability, and the need for solutions tailored to everyone's socioeconomic situation [16], [17]. AI technology is better at making predictions than traditional models, and it can help improve resource efficiency as well as the economy, environment, and society in general when it comes to waste management [18].

Recent advancements in waste classification have improved accuracy and efficiency by applying various machine learning techniques. The overall performance of the support vector machine (SVM) in the waste categorization problem shows that the classification results of waste photos with scale-invariant feature transform (SIFT) feature extraction yield an accuracy value of 62%, which is better than adding the principal component analysis (PCA) method to reduce the dimensionality of the feature data [19]. Additionally, deep learning methods, particularly convolutional neural networks (CNNs), are used in smart solid waste classification, achieving 87% accuracy using a pre-trained CNN model residual network with 50 layers (ResNet-50) [20]. Although deep learning models have shown superior performance, achieving up to 97.53% accuracy for waste classification, reviews indicate that previous studies often lacked critical synthesis, tended to focus on controlled datasets, and overlooked limitations in generalization when applied to real-world environmental variability. Applying CNN for automatic waste classification using image data and directly learning hierarchical features from pixel values [21]. Additionally, comparative studies have been conducted between deep learning models and conventional approaches. One study on autonomous waste sorting between deep learning and SVM emphasized the better performance of deep learning models under certain conditions [22]. CNN-based automatic waste sorting system to simplify waste management techniques [23], by managing various types of waste according to waste categorization and investigating several architectural designs to find the best performance [24].

Using CNNs, recent research has revealed that it is now much easier to distinguish between organic and inorganic materials. Research shows that advanced CNN architectures can categorize everyday object materials with an average accuracy of up to 94.99% using three popular material datasets: Flickr material dataset (FMD), materials in context database (MINC)-2500, and ImageNet7 [25]. The CNN ResNet-50 architecture optimized with a genetic algorithm achieved 97.53% accuracy in classifying organic and inorganic waste [26]. Meanwhile, systematic evaluation of CNN architectures combined with SVM classifiers demonstrated that transfer learning approaches can achieve approximately 92.5% mean average precision on the MINC-2500 material database, validating the efficacy of hybrid deep learning-classical machine learning pipelines for material recognition tasks [27]. A new method has been developed to use CNNs to transform classic Gabor filters. This makes material recognition more accurate without slowing down processing performance [28]. Researchers have created a multi-scale CNN that can classify materials in X-ray images. This works better than regular CNN architectures [29]. CNN has also been used to make quantitative predictions about organic compounds using near-infrared spectra, and the results are quite good, with an R-squared (R^2) value of 0.9955 [30]. This new development has significantly enhanced the material's ability to distinguish between organic and inorganic compounds.

To further improve classification accuracy, research has been conducted that combines deep learning models with other machine learning approaches, such as CNN combined with random forest, k-nearest neighbors, naive Bayes, and SVM [31]. CNNs application has also been expanded to categorize organic and solid waste, highlighting their efficiency in addressing environmental management issues [20]. A new integrated deep learning model for smart waste categorization and a robust solution for effective waste management has recently emerged [32]. Additionally, it is recommended to improve the accuracy and efficiency of sorting in real-world settings using a deep learning-based CNN intelligent waste categorization system [33].

AI model success depends heavily on training data quality and availability, which are scarce in the real world. Public camera monitoring also raises critical privacy concerns. Additionally, existing research

primarily focuses on classification accuracy, overlooking dynamic environmental factors like material types and changing lighting. Consequently, these models face reproducibility and generalization issues during real-world implementation. This stems from environmental variability, including shifting lighting and observation angles, which previous studies frequently ignore.

This study evaluates CNN performance in diverse settings to improve waste classification. CNNs flexibly process various inputs, including images, X-ray scans, and near-infrared spectra. Through a comprehensive literature review, this research analyzes the interaction between material characteristics, lighting, and viewing angles. A CNN architecture is selected for its effective hierarchical feature extraction from images. By focusing on these environmental variables, the study aims to develop a robust model capable of handling real-world operational challenges.

2. PROPOSED METHOD

The model explicitly addresses real-world environmental variables such as detection time, lighting intensity, and observation angle to maximize operational robustness. The architecture features three 2-dimensional convolutional layer (Conv2D) and pooling layers to efficiently simplify data and capture critical visual features. Trained on over 1,000 diverse samples, the system utilizes data augmentation, dropout layers, and ridge (L2) regularization to prevent overfitting on a limited dataset. Performance is rigorously evaluated using accuracy, precision, recall, F1-score, and a confusion matrix [34]. The methodology spans data collection, model development, training, and testing phases to deliver a reliable solution. Finally, the analysis considers ethical implications and practical integration into automated waste sorting systems.

2.1. Data collection

Organic, inorganic, and background samples were manually annotated. Photographs were taken under ‘bright’ and ‘dark’ lighting conditions to test the model’s sensitivity to light intensity and to simulate real-world object orientations. Additional criteria included detection time to evaluate the efficiency of material recognition. Although the data collection accounted for visual elements (texture, pattern, and color), the limited dataset size and potential class representation imbalances are acknowledged. Developing a CNN model robust to environmental changes relies heavily on this data, though the process entails the need for advanced preprocessing techniques, such as data augmentation and stratified sampling.

2.2. Data preprocessing

This process begins with data cleaning, image dimension standardization, and pixel value normalization. To address the modest size of over 1,049 samples and expand diversity, complex augmentation techniques like rotation, horizontal flipping, and brightness adjustments are applied to underrepresented categories. The dataset is then split into 80% for training and 20% for validation/testing. Stratified sampling ensures proportional representation of organic, inorganic, and background classes across both sets. Given the small dataset size and high visual complexity, this proactive step mitigates class imbalances and training bias, substantially improving generalization and reproducibility.

2.3. Model development

The CNN architecture identifies materials by processing type, lighting, viewing angle, and detection time. It extracts hierarchical visual features directly from pixel values. The network routes inputs through three Conv2D hidden layers utilizing rectified linear unit (ReLU) activation to capture non-linear patterns. The modified output layer applies a softmax function to classify waste into organic, inorganic, or background categories. During training, the Adam optimizer adjusts weights and learning rates based on accuracy-driven loss metrics. To mitigate validation overfitting, the model incorporates dropout layers, L2 regularization, and early stopping. This architecture effectively captures complex object-light interactions to build a highly robust predictive model.

2.4. Training and validation

The stages of the CNN method in finding data patterns involve a training process of 50 epochs, using 80% of the training dataset, with small feature combinations and batch sizes, while 20% of the dataset is used to determine validation loss. The adaptive moment estimation (Adam) optimizer is used to update the model weights. For material classification tasks, the loss function used is accuracy-oriented. Early stopping is a crucial step used to stop the process when validation performance no longer improves, and this technique is applied together with dropout layers and L2 regularization to limit overfitting. This study acknowledge that the validation loss indicates potential generalization issues, so these steps ensure that the resulting model not only accurately learns the patterns of the training data but also has a stronger ability to make consistent predictions on new data.

2.5. Evaluation metrics

Derived from the confusion matrix, these metrics comprehensively evaluate classification capabilities across all organic, inorganic, and background categories. An independent test set comprising 20% of the total dataset ensured generalization on unseen data. The specific formulas for these classification metrics will be presented in (1) to (4). Standard for classification tasks, model performance increases as the values of these indices increase [34].

$$Recall = \frac{TP}{TP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$F1-score = 2 \times \frac{Precision\ x\ Recall}{Precision+\ Recall} \tag{4}$$

TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives. Recall measures the model's ability to find all positive instances, while precision shows the proportion of correct positive predictions. Accuracy reflects overall classification correctness across all classes, and the F1-score balances both precision and recall. A confusion matrix visualizes the distribution of correct and incorrect classifications for each material category. Finally, class-wise performance analysis highlights strengths and weaknesses across categories, utilizing macro-averaging to weight each class equally regardless of dataset representation.

Additionally, if the evaluation framework includes temporal consistency assessment, mean squared error (MSE) in (5), root mean squared error (RMSE) in (6), and mean absolute error (MAE) in (7) were utilized as supplementary metrics to quantify prediction error in detection speed or processing latency.

$$MSE = \frac{1}{n} + \sum_{i=1}^{n} (y\hat{}i - yi)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n} + \sum_{i=1}^{n} (y\hat{}i - yi)^2} \tag{6}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} x_i - x \tag{7}$$

Where n denotes the sample size, y_i represents the observed detection latency, and $\hat{y}_i$ is the predicted latency value. These temporal metrics complement the classification evaluation by ensuring that the model maintains not only classification fidelity but also consistent inference latency in real-world deployment scenarios. Lower temporal metric values indicate superior prediction consistency.

2.6. Result analysis

Analysis results determine model performance during testing and training. The evaluation considers accuracy, prediction errors, and environmental variables like lighting, observation angle, and material type. This identifies weaknesses in low-accuracy categories like organic and background, highlighting areas for data balancing or L2 regularization. Accuracy, precision, and F1-score evaluate consistency and generalization. Additionally, regression metrics (MSE, RMSE, and MAE) assess detection time consistency by quantifying inference latency errors to ensure stable throughput. Visualizations like confusion matrices and true vs. predicted graphs reveal systematic biases in accuracy and latency. This integrated evaluation balances classification robustness with efficiency constraints to meet real-world operational requirements and ethical risks.

3. RESULTS AND DISCUSSION

Study outcomes and thorough analysis aligned with research goals will be presented next. This evaluation focuses on waste management implications, particularly how material characteristics, angles, lighting, and detection time affect the developed CNN model's performance [35].

3.1. Data collection

This research evaluates material categorization performance using a dataset of 1,049 manually annotated custom samples. Images were collected under 'bright' and 'dark' lighting conditions at specific angles (30°, 90°, and 180°) to replicate real-world conditions. Regression metrics assessed detection time to determine system efficiency alongside classification accuracy. The dataset comprises 495 inorganics, 475 organics, and 124 background images. Preprocessing addressed the potential class imbalance indicated by this distribution. To mitigate low accuracy caused by limited diversity in certain classes, data augmentation was applied to better reflect real-world problem complexity.

3.2. Preprocessing

The preprocessing stage supports this CNN architecture by enabling direct extraction of hierarchical visual features from pixels. The model follows a general pattern: [Conv2D + pooling] × 3 → flatten → dense (128) → dropout → dense (3). Three convolutional layers receive 128 × 128 images for automatic feature extraction. Spatial size decreases after each layer while filter depth increases (32 to 128) to learn complex patterns. The flattening layer generates a 25,088-length vector, using ReLU activation for non-linear trends before three output neurons project the final classification. Containing 12,940,355 trainable parameters, the model captures complex dataset trends. To mitigate training overfitting, it incorporates dropout layers and L2 regularization. This compact 12 MB model is ideal for internet of things (IoT) deployment, supporting an automated waste management system.

This CNN model classifies waste into organic, inorganic, and background categories across several testing scenarios, as shown in Figure 1. It recognizes organic visual features like texture and patterns, achieving a 99.83% prediction accuracy in a specific test in Figure 2. Overall test data accuracy reached 83.58%, led by inorganic materials at 83.3%. However, the model faces significant generalization challenges. Specifically, organic accuracy dropped to 58.3% and background accuracy reached only 50%. This lower performance stems primarily from a lack of sufficient training data to cover all real-world variations.

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_12 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_13 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_13 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_14 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_14 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten_4 (Flatten)	(None, 25088)	0
dense_8 (Dense)	(None, 128)	3,211,392
dropout_4 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 3)	387

Total params: 3,305,027 (12.61 MB)
Trainable params: 3,305,027 (12.61 MB)
Non-trainable params: 0 (0.00 B)

Figure 1. The architecture of the CNN model



Figure 2. The model's organic material categorizing prediction results

Overall, these results confirm that CNN-based systems have strong and reliable potential for application in camera-based automatic waste sorting systems (smart waste sorting). However, because the model shows a tendency toward overfitting, performance in weak categories requires improvement thru more aggressive data balancing and data augmentation. Additionally, optimizing the model architecture and applying L2 regularization are crucial for fundamentally improving the model's generalization ability and robustness across various environmental conditions.

3.3. Accuracy evaluation

Figure 3 presents the performance evaluation of the waste classification model categorized by type, lighting, viewing angle, and detection time using (1) through (4). Prediction performance was assessed by comparing results against ground truth values via a binary classification confusion matrix. Inorganic materials yielded the highest accuracy (83.3%) due to their more consistent surface patterns and structures. In contrast, organic materials and background elements recorded accuracies of 58.3% and 50%, respectively, owing to limited training data variation. While highly effective at detecting inorganic waste, the model requires refinement for other categories. Optimization strategies could include balancing the dataset, augmenting data for underrepresented classes, and enhancing the model architecture to capture complex inter-category relationships for real-world application.

Light significantly impacts material categorization accuracy. Figure 4 shows accuracy drops from 80% in "bright" settings to 71.4% in "dark" situations. Higher accuracy under focused lighting indicates the model successfully identifies textures and patterns, while low-light conditions obscure vital visual inputs. This 8.6% drop proves high lighting sensitivity, though the model remains reasonably effective in poor conditions. Object placement angle also influences detection accuracy, as illustrated in Figure 5. Tests reveal the highest accuracy at 0° (75%), followed by 30° (69.44%) and 180° (66.67%). Applying angle-correction preprocessing or augmenting data with extreme angles can enhance reliability in practical applications. Figure 6 illustrates the effect of processing time: the "dark" condition took 78.3 ms, whereas the "light" condition was faster at 72.5 ms, as the object was easier to detect under the "light" condition.

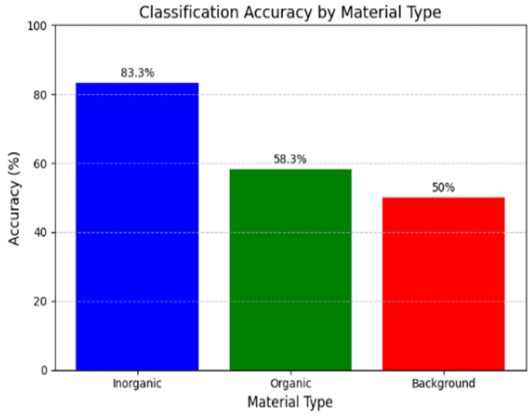

Figure 3. The analysis performed based on the given test data

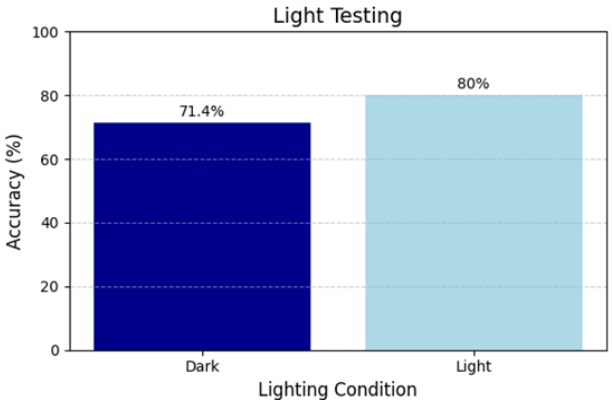

Figure 4. The effect of light on the categorization of materials

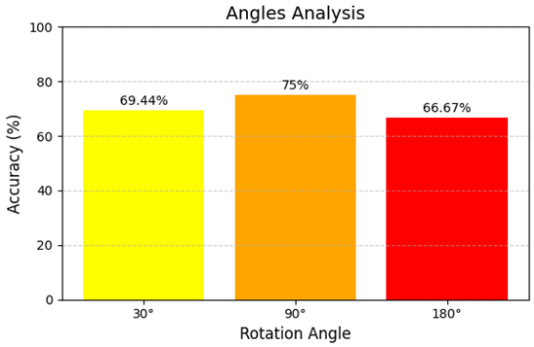

Figure 5. The effect of tilt angle on detection accuracy

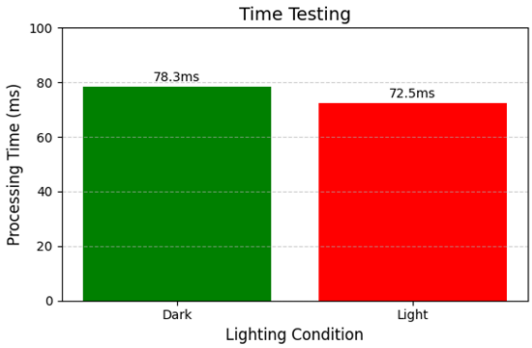

Figure 6. The effect of lighting on detection accuracy

The CNN model achieves 87% overall accuracy in Figure 7, evaluated using precision, recall, and F1-score across 219 test samples. Class-wise analysis shows inorganic materials performed best with a top precision of 0.96, indicating minimal misclassification errors. The background class yielded the highest recall (0.89), demonstrating excellent non-garbage area identification. The organic class maintained balanced performance, with recall and precision both at 0.86. The average F1-score (macro/weighted average) of 0.87–0.88 confirms stable, unbiased performance across all classes. This marks a significant improvement over previous model iterations, which exhibited bias with low organic and background accuracies of 58.3% and 50%, respectively. These high-quality results prove CNN-based systems are highly suitable for AI-powered automated waste sorting. However, the model remains sensitive to environmental variables like lighting and observation angles, which can reduce accuracy. Future enhancements must focus on managing texture and lighting complexity through data augmentation or regularization to ensure consistency in real-world operations.

	precision	recall	f1-score	support
inorganic	0.96	0.87	0.91	30
background	0.86	0.89	0.87	106
organic	0.86	0.86	0.86	83
accuracy			0.87	219
macro avg	0.89	0.87	0.88	219
weighted avg	0.87	0.87	0.87	219

Figure 7. Accuracy of the CNN model

3.4. Confusion matrix

This article analyzes a classification model for a waste material type detection system for 50 cycles, with validation results falling under 0.8, as shown in Figure 8. However, the model faces challenges in validation because of variability and a lack of validation, and there is a potential for overfitting problems. To overcome this, the model that was created was carried out with early stopping, regularization (eg, L2 or dropout), or data augmentation that can be used to improve the model's generalization capacity.

Confusion matrix analysis evaluates class-wise performance, confirming an 87% overall accuracy with 191 correct predictions out of 219 test samples. Specifically, the model classifies inorganic materials well (26 correct predictions). However, its main weakness lies in distinguishing organic materials from the background across 94 background samples due to similar colors or textures. This error pattern aligns with previously reported low accuracies for organic (58.3%) and background (50%) classes. These confusion matrix results provide crucial data for targeted interventions such as data balancing, data augmentation, or regularization to enhance model robustness and generalization.

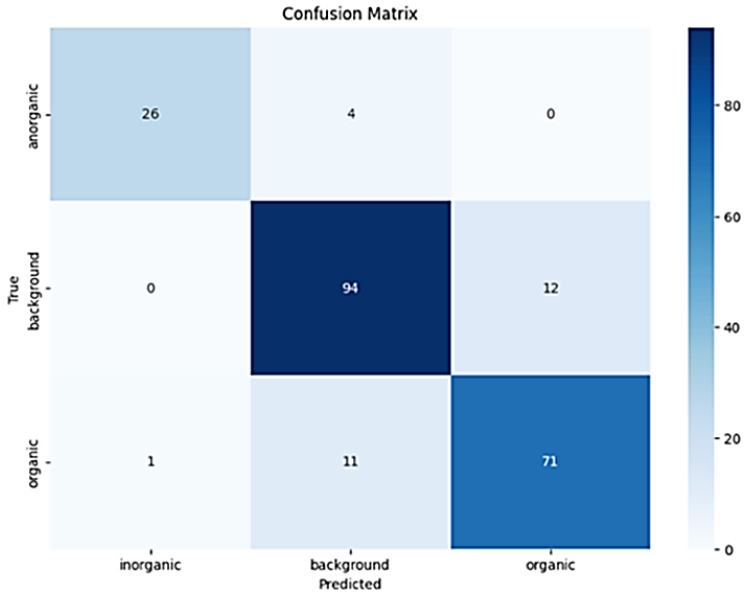

Figure 8. Confusion matrix result

Model evaluation across 50 epochs revealed a dual-constraint optimization problem. Validation accuracy plateaued under 0.8, while temporal metrics (RMSE = 1.0700, MSE = 1.1449, and MAE = 0.9070) indicated substantial detection latency prediction errors. Figure 9 illustrates model loss over epochs. Figure 10 illustrates model MAE over epochs. Analysis of the true vs. predicted values plot demonstrated widespread deviation from the ideal diagonal line, reflecting systematic prediction bias and high variance in latency estimation. The MAE of 0.91-time units masks significant heterogeneity in prediction accuracy across material categories and environmental conditions. Material types under variable lighting and observation angles exhibited errors exceeding this mean, signifying non-uniform performance degradation across operational scenarios. Together, these classification and temporal findings point to a common cause: inadequate training data diversity and potential overfitting, where the model learned dataset-specific patterns without generalizing to unseen conditions.

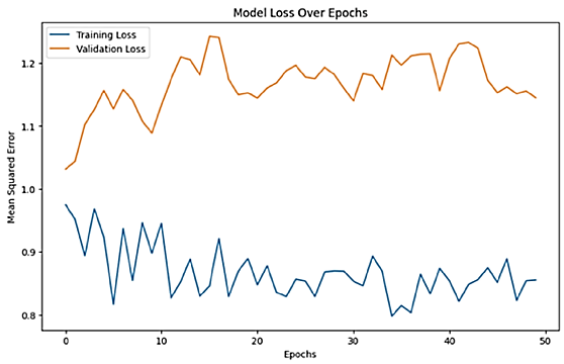

Figure 9. Model loss over epochs

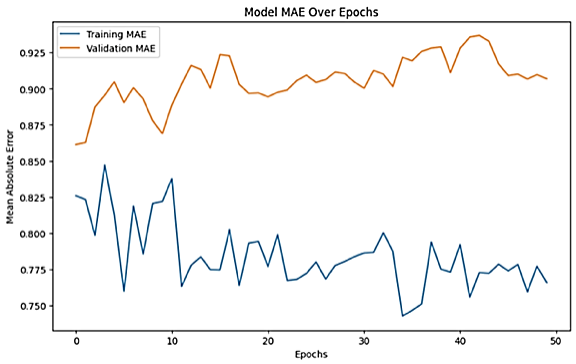

Figure 10. Model MAE over epochs

Remediation required addressing classification and inference latency as coupled rather than independent objectives. Strategic interventions encompassed targeted data augmentation for underrepresented material-environment combinations, regularization mechanisms (L2 and dropout), and adaptive early stopping to arrest both classification and temporal overfitting simultaneously. By reframing the optimization problem as a joint maximization of classification discriminability and latency prediction consistency rather than isolated metric improvement, the model can achieve the generalization capacity requisite for real-world deployment. As shown in Figure 11, this dual approach ensures operational feasibility in automated sorting applications where both accuracy and processing stability are critical.

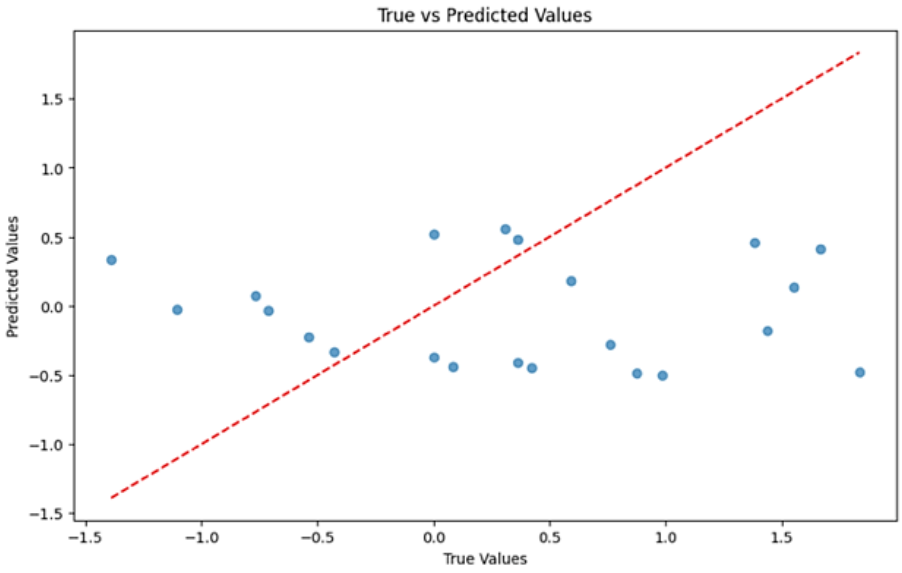

Figure 11. True vs predicted values

4. CONCLUSION

The material classification model excels at identifying inorganic materials but struggles with organic and background elements. Its performance is heavily influenced by environmental factors like lighting and viewing angle, achieving peak accuracy under optimal lighting and specific material orientations. However, signs of overfitting are present, as the model performs well on training data but struggles to generalize to validation data. Optimizing through data augmentation, regularization, and architectural adjustments can transform it into a reliable solution for automated material detection systems in recycling and manufacturing. This study stands out by deeply analyzing lighting, viewing angles, and detection time factors often overlooked in similar research. Future work should focus on preprocessing algorithms like contrast enhancement to improve low-light performance, alongside data augmentation combining various angles and lighting scenarios. Additionally, exploring advanced techniques like transformers or attention mechanisms can enhance the model's capacity to understand complex material relationships, fulfilling the goal of developing a robust, flexible model for real-world deployment.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [ERA]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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