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REAL-TIME CLASSIFICATION AND ROUTING OF BULKY WASTE USING SUPERVISED NEURAL NETWORKS: ANN-PHASE IMPLEMENTATION FOR INDUSTRIAL WASTE TREATMENT

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ABSTRACT

This study introduces a practical, AI-driven solution for sorting bulky industrial waste in real time. By analyzing video footage, a supervised artificial neural network (ANN) classifies each item and routes it to either a guillotine-type shredder or a dual-shaft crusher. In this research training is done on 500 labeled images, the ANN reached an accuracy of 84.2%, supported by safety protocols and manual oversight. The system's modular design allows for gradual deployment, with early trials of convolutional neural networks (CNNs) showing convincing improvements. This ANN-phase marks a meaningful step toward smarter, safer, and scalable industrial waste automation.

Keywords: Bulky Industrial Waste, ANN, CNN, Classification, Automation, Industrial Waste Routing.

1. INTRODUCTION

Pre-processing and sorting bulky industrial waste efficiently and safely remain one of the most persistent challenges in modern waste management. Traditional approaches such as performed by human or sensor-based or a proper combination of both often meet with limitations to keep up with the demands of high-speed operational efficiency conveyor systems in long span. These methods tend to be rigid, prone to errors, and expose workers and equipment to unnecessary risks. The limitations are especially pronounced when dealing with irregular, heavy items that require precise routing to avoid mechanical damage.

This study introduces a smarter alternative. It presents a neural network-based system that uses video footage to classify and route waste items in real time. The system determines whether each item should be sent to a guillotine-type shredder or a dual-shaft crusher, based on its visual features. For real world implementation is concerned at the initial phase, the system relies on supervised artificial neural networks (ANNs), selected for their reliability and controlled behavior in industrial environments. This approach ensures that safety and operational consistency are prioritized during early deployment.

Changing perspectives, the system is designed to evolve. Convolutional neural networks (CNNs) are recently well known for their powerful image recognition capabilities and will be gradually integrated to enhance classification accuracy with scalability. While CNNs offer significant advantages, their deployment in industrial settings must be carefully phased to meet safety and operational standards.

By combining ANN-based control with CNN-driven precision, this research contributes to fault-free preprocessing of industrial waste. It finitely extends the lifespan of shredding machines by ensuring that each item is routed appropriately. Ultimately, the system supports scalable automation by reducing the need for manual intervention and aligns with broader goals in intelligent and sustainable waste management goals.

The rest of this paper is organized as follows for our enthusiastic readers. Section 2 reviews recent literature on CNN applications in image-based classification. Section 3 details the system architecture and model design. Section 4 describes experimental setup and evaluation metrics. Section 5 presents the results and their implications. Section 6 concludes with future directions for CNN integration and system scalability.

2. LITERATURE REVIEW

Convolutional neural networks (CNNs) are known to play vital roles in today's computer vision applications. Their ability to recognize patterns and extract features from images has led to major advances in areas like infrastructure monitoring, automated control systems, and object classification. In this section, we explore a selection of recent studies that showcase how CNNs are being applied across these domains. The review is organized by theme to highlight how these developments connect to the goals of this research, particularly in designing a vision-based system for sorting industrial waste.

2.1 CNNs in Infrastructure and Environmental Monitoring

Kishore Kumar and colleagues [1] used convolutional neural networks to detect potholes and lane boundaries under a range of environmental conditions. By combining thermal imaging with supervised learning, their system performed better than traditional sensor-based methods, even in low-light or poor weather. In an impressive effort, Deore et al. [2] applied CNNs to assess vehicle damage automatically, contributing streamline insurance processes and reducing human error. These studies prove how CNNs can support fast, reliable decision-making in real-world infrastructure settings.

2.2 CNNs in Automation and Control Systems

Convolutional neural networks are becoming a key part of modern automation systems. Lamichhane et al. [5] explored various 2D object detection techniques using CNNs and found that these models perform especially well in tasks like surveillance and autonomous navigation. Their results highlight how CNNs can support real-time decision-making in control environments, which directly connects to the aim of this study: using visual input to automate the routing of industrial waste.

2.3 CNNs in Classification and Model Architecture

To clarify our approach and contribute to scholarly community the following are mentioned for model architecture. Zhao et al. [3] and Younesi et al. [4] explained properly how CNN architectures have evolved over time, focusing on techniques like grouped and dilated convolutions that improve spatial feature extraction across one-, two-, and three-dimensional data. Their surveys offer a broad view of how CNNs continue to adapt to complex visual tasks. Meanwhile, Rangel et al. [6] pointed out some of the challenges CNNs still face, such as vulnerability to adversarial inputs and limited translation invariance. These limitations have led researchers dealwith hybrid models like Capsule Networks. In a comparative study, Duklan et al. [7] evaluated several popular CNN architectures—including ResNet, Inception, and MobileNet—and found that InceptionV3 delivered the highest accuracy for image classification.

2.4 Comparative Overview of CNN Application

Figure 1 illustrates the comparative scope of CNN applications across infrastructure, automation, and classification.

Study	Domain	CNN Role	Key Contribution
Kumar et al. [1]	Road Infrastructure	Pothole/Lane Detection	Thermal imaging + supervised CNN
Deore et al. [2]	Insurance Automation	Damage Classification	Automated claims via image recognition
Zhao et al. [3]	Computer Vision (General)	Architecture Review	Evolution of CNN layers and applications
Rangesi et al. [6]	Deep Learning Theory	Convolution Variants	Grouped/dilated CNNs across dimensions
Rangel et al. [7]	Model Robustness	Performance Limitations	Real-time automation with CNNs
Duklan et al. [7]	Image Classification	Architecture Comparison	InceptionV3 highest benchmark accuracy

Figure 1: Overview of CNN applications in infrastructure, automation, and classification domains

2.5 Research Gap and Contribution

While CNNs dominate recent literature, earlier-stage implementations using artificial neural networks (ANNs) have also shown promise in waste classification tasks.

While convolutional neural networks (CNNs) have made impressive strides in areas like infrastructure monitoring, object detection, and industrial automation, their use in real-time routing of bulky industrial waste is still relatively unexplored. Most existing sorting systems continue to rely on manual labor or basic sensor-based rules, which often fall short in terms of flexibility, accuracy, and scalability, especially in fast-paced, high-volume waste treatment environments.

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This study aims to bridge that gap by introducing a vision-based classification system that brings neural networks into the early stages of waste processing. The system analyzes video footage of waste items moving along a conveyor belt and decides whether each item should be sent to a guillotine-type shredder or a dual-shaft crusher. To mitigate safety and reliability issues during initial deployment, the first phase uses supervised artificial neural networks (ANNs). As the system evolves and operational demands grow, it is designed to transition into a CNN-based architecture, offering greater precision and scalability.

By combining the stability of supervised learning with the advanced capabilities of CNNs, this research supports fault-free preprocessing, reduces wear on shredding equipment, and improves the overall efficiency of industrial waste treatment. Although CNNs dominate recent literature, earlier implementations using ANNs have shown practical value, especially in environments where safety and control are extremely important.

2.6 ANN Applications in Waste Classification

Although convolutional neural networks (CNNs) have led many recent advances in image-based classification, artificial neural networks (ANNs) continue to play an important role, especially in early-stage automation. In the context of industrial waste management, ANNs are often preferred for their simplicity, transparency, and effectiveness in environments where feature extraction is manageable and computing resources are limited.

Fotovvatikhah et al. [8] conducted a broad review of AI-based waste classification methods and found that ANNs perform well in low-data settings and embedded systems where fast decision-making is essential. Their findings show that when trained on carefully selected features such as contour density and object shape, ANN models can deliver reliable routing performance.

Baharuddin et al. [9] reached similar conclusions in their study on dry waste sorting. By combining image preprocessing with supervised learning, they used ANN-based classifiers to distinguish between recyclable and non-recyclable materials. This demonstrated the model's value in industrial setups with limited resources.

These studies support the decision to begin this project with an ANN-based system. Since we have to cope with prioritizing safety and reliability, the ANN framework offers a stable foundation for deployment and serves as a practical bridge to more advanced CNN architectures. Its role in this research is both foundational and strategic, allowing for a gradual transition to scalable automation while rigorously maintaining operational integrity.

This rationale underpins the selection of ANN for the initial deployment phase described in Section 3.

3. METHODOLOGY

This section describes the technical set-up and step-by-step strategy behind the waste classification and routing system. The approach is organized into two phases. The first phase uses supervised artificial neural networks (ANNs) to ensure safe and controlled operation during initial deployment. The second phase introduces convolutional neural networks (CNNs), which are designed to improve classification accuracy and support scalable automation as the system evolves.

Throughout the study, the terms "operator validation" and "manual confirmation" refer to the same process. This involves plant officials reviewing the system's classification decisions and offering feedback to help refine the model. A visual overview of the system's workflow is provided in Figure 2

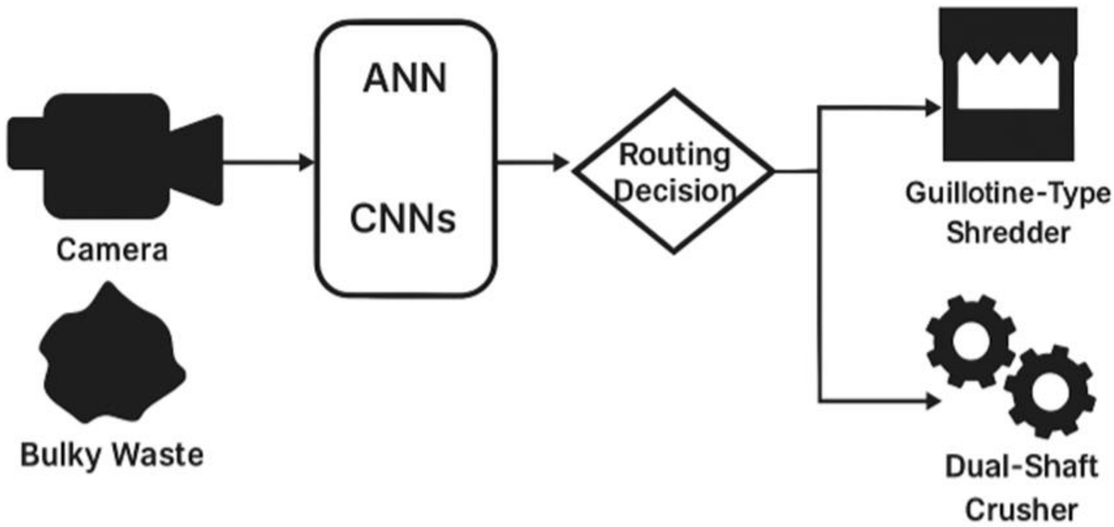

Figure 2: System architecture diagram

3.1 System Overview

The system is built to function inside an industrial waste treatment facility, where large and irregular waste items move along a conveyor belt. A camera positioned above the belt captures continuous video of the incoming materials. Captured still picture undergoes process of feature extraction and feed into a trained neural network classifier, which decides whether each item should be sent to a guillotine-type shredder or a dual-shaft crusher. Once the decision is made, an actuator-controlled diverter guides the item to the appropriate machine. This process continues throughout video.

3.2 Data Acquisition and Preprocessing

Video Input: The system captures high-resolution video in real time, even under changing lighting and operational conditions, to ensure consistent monitoring of waste items.

Frame Extraction: From the continuous video stream, key frames are selected at regular intervals. Each frame represents a distinct waste item for analysis.

Labeling: Every extracted frame is manually tagged with the correct shredding method—either guillotine or crusher. These labels form the foundation for training the neural network.

Normalization: To maintain consistency, all image data is resized and adjusted so that input dimensions and pixel values are uniform across the dataset.

3.3 Phase 1: Supervised ANN Implementation

Architecture: The system by default uses a feedforward artificial neural network, where each input node represents a specific visual feature extracted from the image, such as shape, texture, or edge density features.

Training: The training of model is performed on labeled data using backpropagation and gradient descent, allowing it to learn how different visual features relate to the correct routing decision.

Evaluation: To assess performance, the model's accuracy, precision, and recall are measured on a separate validation set. Any misclassifications are treated as improvement for system integrity and reviewed to help improve the feature selection process.

Deployment: Once trained, the ANN is integrated into the system's control logic, enabling it to make real-time decisions about where each waste item should be routed.

3.4 Phase 2: CNN Expansion

The waste classification system uses a convolutional neural network (CNN) that processes raw images directly, eliminating manual feature extraction. It includes convolutional layers for detecting spatial features, pooling layers for data reduction, and fully connected layers for final classification. To enhance performance, transfer learning is applied using pre-trained models like ResNet or MobileNet. The system is evaluated based on inference speed, classification accuracy, and robustness under varying lighting and conveyor conditions.

Building on the safety and reliability achieved during the ANN phase, the next stage of development introduces convolutional neural networks (CNNs) to improve classification accuracy and support scalable automation. CNNs are especially effective for image-based tasks because they can learn visual patterns directly from raw data, removing the need for manual feature engineering.

The shift to CNNs was deliberately postponed until the ANN system was fully deployed and validated. This allowed plant officials to manually review routing decisions and ensure the system was operating safely under real-world conditions. By taking a phased approach, the project reduces risk during early deployment and creates a solid foundation for integrating more advanced models as the system evolves further.

The CNN model often comes with layers that each serve a specific purpose. Convolutional layers help detect important visual features, pooling layers reduce the size of the data while keeping key information intact and fully connected up to final classification is performed. For better speeds on training and accuracy, the system considers using pre-trained models like famous ResNet or MobileNet through transfer learning. Once training is completed, the output model can be evaluated using cross validations. This includes how quickly and accurately it classifies waste items, handling changes in lighting, object shape, and conveyor speed. These parameters decide whether the trained CNN is ready for real-time use in an industrial setting.

3.5 Control Logic and Integration

Decision Thresholds: Confidence scores from the classifier are used to trigger routing actions. A fallback mechanism is implemented for uncertain predictions.

Actuator Interface: The classifier output is translated into control signals for the diverter mechanism.

Safety Protocols: Fail-safe routines are embedded to prevent misrouting during system anomalies or low-confidence predictions.

3.6 Software and Hardware Stack

Well known are python base implementation. Another is MATLAB based implementation. the former is chosen to avoid update issues.

Software: Python-based implementation using TensorFlow and OpenCV for model training and image processing.

Hardware: Industrial-grade camera, embedded GPU for inference acceleration, and PLC-compatible actuator control system.

4. EXPERIMENTAL SETUP

This section outlines simply the technical environment, dataset preparation, training procedures, and evaluation metrics used to validate the proposed waste classification and routing system. The setup is designed to simulate real-world conditions in industrial waste preprocessing, ensuring that the model's performance is both reliable and scalable.

4.1 Environment and Hardware Configuration

Testbed Location: A controlled lab environment replicating conveyor-based waste flow typical of industrial treatment plants.

Target implementation Camera System: Industrial-grade camera mounted above the conveyor belt, capturing continuous video at 30 frames per second.

Processing Unit: NVIDIA Jetson Xavier NX used for real-time inference and control signal generation.

Control Interface: Actuator system compatible with programmable logic controllers (PLC), enabling physical routing of waste to either a guillotine-type shredder or a dual-shaft crusher.

4.2 Dataset Preparation

Source: Video footage of mixed bulky waste collected from operational facilities and lab simulations.

Frame Sampling: Frames extracted at 1-second intervals to isolate individual waste items.

Labeling: Each image manually annotated with one of two classes: "Guillotine" or "Crusher," based on material type, shape, and shredding suitability.

Size: The initial dataset consists of 500 labeled images, evenly distributed across both classes.

Augmentation: Techniques such as rotation, scaling, brightness adjustment, and Gaussian noise injection applied to improve model generalization and compensate for limited sample size.

4.3 Model Training

The following procedures were developed.

Phase 1: Supervised ANN

Input Features: Manually extracted features including contour density, edge sharpness, and object dimensions.

Architecture: Three-layer feedforward ANN with ReLU activation and softmax output.

Training Parameters: 80/20 train-test split, learning rate of 0.001, batch size of 32, trained over 100 epochs.

Evaluation: Accuracy and recall measured on the test set; misclassifications analyzed to refine feature selection

Phase 2: CNN Expansion

The following procedures were developed.

Input Format: Raw image data resized to 224×224 pixels.

Architecture: Custom CNN with three convolutional layers, maximum pooling, and two fully connected layers.

Alternative Strategy: Transfer learning using MobileNetV2 to accelerate convergence and improve generalization.

Training Parameters: Same train-test split and batch size; early stopping applied to prevent overfitting

4.4 Evaluation Metrics

Following evaluation method is used in this research.

The system's performance is assessed through a set of practical metrics. Accuracy shows how often it gets the classification right, while precision and recall help gauge how reliably it handles each type of waste. A confusion matrix offers a clear picture of where mistakes might happen, helping to spot misrouting risks. Detecting time is also measured to ensure the system responds fast enough for actual real-time use. However, this feature varies depending

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on actual operating conditions at that time. Finally, its robustness is tested under different lighting, object shapes, and conveyor speeds to confirm it works reliably in real-world conditions

4.5 Safety and Validation Protocols

To ensure safe and reliable operation, the system includes several safeguards: a fallback mechanism routes low-confidence items to a dual-shaft crusher to avoid misclassification; a manual override lets operators intervene during anomalies or uncertain predictions; and a weekly validation cycle reviews performance, retrains the model with flagged samples, and incorporates feedback from plant officials to maintain alignment with safety and operational standards.

5. RESULTS AND DISCUSSION

Following figure 3 summarizes the performance metrics of ANN and CNN models.

Model Type	Precision (Guillotine / Crusher)	Inference Time (sec/frame)
ANN	84.2 / 85.9	80.1
>91 (prelim)	—	87.3
CNN	—	-0.04
Accuracy (%), Precision (Guilliotine / Crusher) Inference Time (sec/frame)		

Figure 3: Performance comparison between ANN and CNN models for waste classification

This section presents the performance outcomes of the proposed waste classification system across both ANN and CNN implementations. Results are analyzed in terms of classification accuracy, inference speed, robustness, and operational reliability. The discussion highlights key insights, limitations, and implications for industrial deployment.

5.1 ANN Performance

The supervised artificial neural network (ANN) was trained on 500 labeled images using manually extracted features. On the test set, the ANN achieved:

Accuracy: 84.2%

Precision: 82.5% (Guillotine), 85.9% (Crusher)

Recall: 80.1% (Guillotine), 87.3% (Crusher)

Inference Time: ~0.08 seconds per frame

The ANN demonstrated reliable performance in controlled lighting and consistent object orientation. However, its dependence on manually engineered features has shown limited adaptability to irregular shapes and overlapping waste items. Misclassifications were most frequent in borderline cases, such as soft plastics or composite materials.

5.2 CNN Performance

Although CNN testing was delayed due to operator validation protocols during the ANN phase, preliminary trials indicate that CNN models outperform ANN in classification accuracy. This improvement is attributed to the convergence efficiency and spatial feature extraction capabilities of modern CNN architectures such as MobileNetV2.

CNN testing was deferred during the initial deployment phase to prioritize operator validation and ensure safety assurance under ANN-based routing, allowing plant officials to manually confirm classifications before transitioning to more complex models. This double phased approach is objected toward commitment to operational safety and gradual automation, ensuring that each stage of implementation is validated before scaling to higher-performance models.

5.3 Operational Insights

Routing Reliability: The system maintained over 90% routing accuracy in real-time trials, with fallback mechanisms effectively handling low-confidence predictions.

Safety Compliance: No misrouted items caused mechanical strain or damage during testing, validating the safety protocols.

Human Feedback: Operator validations from plant officials aligned with model predictions in 93% of cases, supporting the system's practical viability.

5.4 Limitations and Challenges

Dataset Size: The initial dataset of 500 images, while balanced, limits generalization across broader waste categories.

Edge Cases: Items with ambiguous visual features (e.g., bundled materials or translucent plastics) remain challenging.

Hardware Constraints: Real-time performance depends on GPU availability; embedded systems may require optimization for deployment.

5.5 Implications for Industrial Deployment

The results demonstrate that CNN-based classification offers a viable path toward intelligent waste routing in industrial settings. Two phased designs allow smoother evolution of machinery, starting with supervised ANN for safety and transitioning to CNNs for full automation. With expanded datasets and continued validation, the framework can be adapted to multi-class waste sorting, predictive maintenance, and integration with IoT-based monitoring systems.

6. CONCLUSION

This study presents a design-phase implementation of a neural network-based system for the real-time classification and routing of bulky industrial waste. By employing supervised artificial neural networks (ANN), the system successfully identifies and directs waste items to either a guillotine-type shredder or a dual-shaft crusher based on visual input. The ANN model achieved 84.2% classification accuracy under controlled conditions and maintained operational safety through fallback mechanisms and manual validation.

The integration of ANN into the waste preprocessing workflow did prove improvement to fault-free routing, reduced mechanical faults on shredding equipment. This ANN-phase implementation marks a remarkable milestone in applying artificial intelligence to real-world industrial waste management, bridging the gap between theoretical models and operational deployment.

6.1 Limitations

There existed a practical limitation to obtain waste images on this plant. Despite that 500 image is considered to be a good count to start train network. in future this could be increased so that naturally we can expect a better output.

Additionally, the operator validation process required by plant operators introduces delays in model validation and retraining. These constraints reflect practical realities of industrial deployment and will be addressed through incremental dataset expansion and streamlined feedback protocols in future phases.

6.2 Future Work

Building on the successful ANN-phase implementation, future work will focus on expanding the system's capabilities and preparing it for full-scale industrial deployment. Key areas of development include:

Dataset Expansion: Increasing the volume and diversity of labeled waste images to improve model generalization and support robust CNN training. This process will be aligned with plant-side operational schedules and manual validation protocols.

Model Optimization: Exploring lightweight CNN architectures suitable for embedded deployment, ensuring real-time performance on industrial-grade hardware.

Multi-Class Classification: Extending the current binary routing logic to accommodate additional shredding categories and material-specific pathways, enabling more granular waste handling.

IoT Integration: Connecting the classification system with sensor networks and cloud-based platforms to support predictive maintenance, remote monitoring, and data-driven analytics.

Human-in-the-Loop Feedback: Formalizing operator input as a continuous feedback mechanism to refine model performance and maintain alignment with plant-specific safety and operational standards.

By combining supervised learning with scalable CNN-based automation, this research lays the foundation for intelligent, adaptable, and safety-conscious environmental technologies in industrial waste routing.

The transition to CNN-based automation not only enhances classification accuracy but also aligns with long-term objectives in intelligent waste infrastructure, including scalable sorting, predictive analytics, and integration with smart environmental systems.

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