MULTISTAGE WASTE CLASSIFIER USING DEEP LEARNING

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Abstract: Efficient waste segregation is a crucial requirement for sustainable solid waste management and environmental protection. Manual waste sorting methods are labor-intensive, error-prone, and ineffective when dealing with large-scale and diverse waste streams. Conventional automated waste classification systems often rely on flat multi-class models, which suffer from poor scalability, class imbalance, and reduced accuracy for visually similar waste categories. This paper presents a hierarchical waste classification system that integrates deep learning-based feature extraction with ensemble Extreme Learning Machines (ELM) to achieve accurate and reliable waste categorization.

The proposed system employs a ResNet-based convolutional neural network for extracting high-level visual features from waste images. Classification is performed in three stages: (i) biodegradable versus non-biodegradable classification, (ii) material-level categorization into nine broad waste groups, and (iii) fine-grained classification into thirty-six detailed waste categories. Feature standardization and ensemble ELM classifiers are used at each stage to improve generalization and computational efficiency. The system is deployed using a FastAPI-based backend and containerized using Docker for reproducible and scalable inference. Experimental results demonstrate reliable performance on unseen waste images with confidence-aware predictions, making the system suitable for smart waste management and environmental monitoring applications.

***IndexTerms* - Waste Classification, Deep Learning, ResNet, Hierarchical Classification, Smart Waste Management**

INTRODUCTION

The rapid increase in urban population and industrialization has led to a significant rise in municipal solid waste generation. Improper waste segregation poses serious environmental and public health challenges, including pollution, inefficient recycling, and increased landfill usage. Automated waste classification systems aim to address these challenges by identifying and categorizing waste materials using image-based techniques.Traditional waste sorting systems rely on manual labor or rule-based automation, which lack adaptability and accuracy. Early machine learning approaches utilized handcrafted features such as color histograms and texture descriptors, but these methods performed poorly under varying lighting conditions and complex backgrounds. With the advancement of deep learning, convolutional neural networks (CNNs) have demonstrated superior performance in image classification tasks by automatically learning discriminative features.

However, most existing deep learning-based waste classification systems adopt a single-stage flat classification approach. As the number of waste categories increases, flat models struggle with visual similarity among classes, leading to reduced confidence and misclassification. This motivates the need for a structured classification strategy that decomposes the problem into multiple simpler decision stages. This research proposes a hierarchical waste classification framework that combines deep feature extraction with ensemble learning to improve accuracy, scalability, and interpretability.

The proposed system is designed not only for high classification performance but also for practical deployment, making it suitable for real-world applications such as smart waste bins, recycling centers, and environmental monitoring systems.

NEED OF THE STUDY.

Improper waste segregation remains a major bottleneck in achieving effective recycling and sustainable waste management. Mixed waste streams increase processing costs, reduce recycling efficiency, and pose environmental hazards. Automated waste classification systems are essential to overcome these limitations.

While deep learning–based waste classification has shown promising results, most existing solutions focus on single-stage or flat classification architectures. These approaches are not well-suited for large-scale waste categorization involving multiple fine-grained classes. Additionally, many models lack interpretability and are difficult to deploy in real-time systems.

This study addresses these limitations by proposing a hierarchical classification framework that improves scalability, enhances interpretability through stage-wise predictions, and supports real-time deployment. The combination of deep learning and ensemble ELM classifiers offers a balance between accuracy and computational efficiency, making the system suitable for practical implementation.

RESEARCH METHODOLOGY

The methodology section outline the plan and method that how the study is conducted. This includes Universe of the study, sample of the study,Data and Sources of Data, study's variables and analytical framework. The details are as follows;

3.1 Dataset and Data Preparation

The waste image dataset used in this study consists of a large collection of images representing commonly encountered waste materials in real-world environments. The dataset covers a wide range of waste categories and includes variations in object size, orientation, lighting conditions, and background complexity. Such diversity ensures that the trained model generalizes well to unseen data.

To support the hierarchical classification strategy, the dataset is organized into three levels corresponding to the three stages of classification. Images are first labeled as biodegradable or non-biodegradable, then grouped into nine material-level categories, and finally classified into thirty-six fine-grained waste classes.

Prior to training, all images undergo preprocessing steps including resizing to a fixed resolution, normalization of pixel values, and data augmentation. Augmentation techniques such as rotation, flipping, and minor scaling are applied to reduce overfitting and improve robustness. The dataset is divided into training, validation, and testing subsets using standard splitting techniques to ensure unbiased performance evaluation and reliable model assessment.

3.2 System Architecture

The system architecture is designed as a multi-stage hierarchical pipeline that processes input images sequentially. The architecture consists of three interconnected classification stages, where each stage refines the output of the previous one. At every stage, a deep convolutional neural network based on the ResNet architecture is used to extract discriminative visual features from the input image.

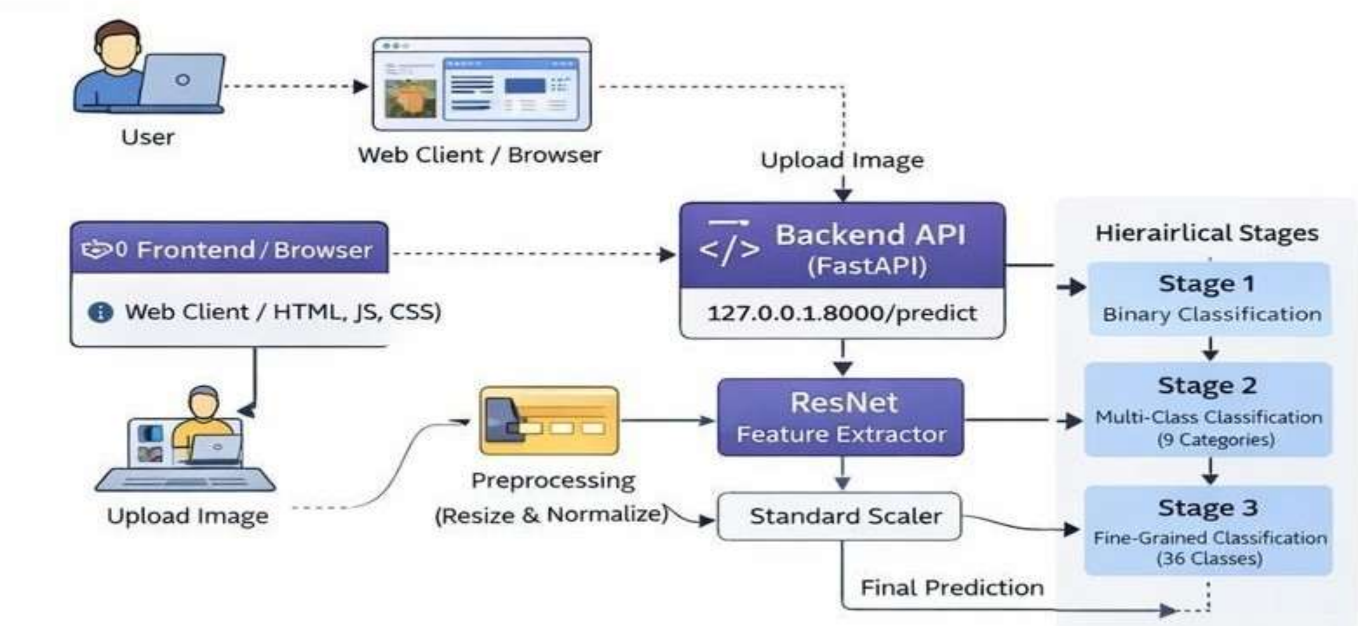

Figure 3.1: Overall architecture of the proposed hierarchical waste classification system

The extracted feature representations are then passed to an ensemble of Extreme Learning Machine classifiers for final decision-making at that stage. By forwarding only relevant samples to subsequent stages, the architecture reduces unnecessary computation, minimizes classification ambiguity, and improves overall system efficiency. This modular design also enables independent optimization and evaluation of each classification stage.

3.3 Hierarchical Classification Strategy

The proposed system follows a hierarchical classification strategy to decompose a complex multi-class waste classification problem into simpler sub-problems. In Stage 1, the system performs coarse-level classification by separating waste images into biodegradable and non-biodegradable categories. This initial segregation reduces class overlap and simplifies downstream processing.

In Stage 2, the output of Stage 1 is further classified into nine intermediate material-based categories, such as recyclable waste, glass, metal, polymer-based materials, and medical waste. This stage captures broader material properties and refines the classification decision.

In Stage 3, fine-grained classification is performed across thirty-six detailed waste categories, enabling precise material identification. This hierarchical decomposition improves interpretability, reduces error propagation, and enhances scalability compared to flat classification approaches.

3.4 Feature Extraction Using ResNet

A Residual Neural Network (ResNet) architecture is employed for feature extraction due to its proven effectiveness in deep image representation learning. ResNet introduces residual connections that allow gradients to flow directly through the network, mitigating the vanishing gradient problem and enabling stable training of deep architectures.

The network learns high-level visual features such as texture patterns, edge structures, color distributions, and object shapes from waste images. These features are extracted from the final convolutional layers and flattened into numerical feature vectors. The extracted representations provide a compact and discriminative description of the input image and serve as input to the classification models.

3.5 Classification Using Ensemble Extreme Learning Machines

Descriptive statistics are used to analyze the distributional properties of the deep feature vectors extracted from the convolutional neural network. The extracted features represent high-dimensional numerical encodings of waste images, capturing visual characteristics such as texture, shape, color distribution, and structural patterns.

Statistical measures including mean, standard deviation, minimum, and maximum values are computed for the extracted feature vectors to examine their spread and central tendency. Feature normalization is applied using standard scaling to ensure that all features contribute proportionally during classification. Normalized feature distributions improve numerical stability and enhance the performance of the Extreme Learning Machine classifiers.

The statistical distribution of feature values provides insight into feature sensitivity and variance across waste categories. Well-distributed feature representations indicate that the model effectively captures discriminative visual patterns required for hierarchical waste classification.

3.6 Deployment Framework

The trained models are deployed using a FastAPI-based backend that exposes the classification functionality through RESTful APIs. This allows real-time inference and seamless integration with frontend applications. The deployment architecture supports hierarchical prediction, returning stage-wise classification results and confidence scores for transparency.

Docker is used to containerize the application environment, ensuring consistent execution across different systems. Containerization improves portability, reproducibility, and ease of deployment, making the system suitable for real-world waste management applications and scalable deployment scenarios.

IV. RESULTS AND DISCUSSION

4.1 Performance Evaluation

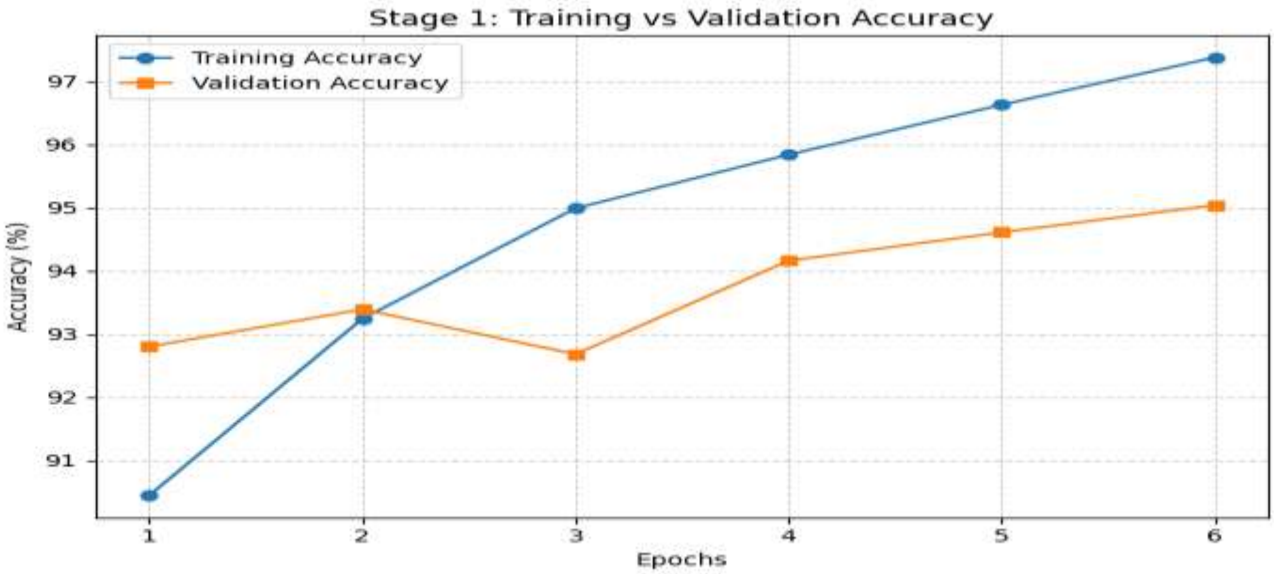

Figure 4.1: Training and validation accuracy across Stage 1

The experimental results demonstrate strong performance across all three stages of the hierarchical classification system. Stage 1 achieves the highest accuracy due to its binary classification nature, effectively separating biodegradable and non-biodegradable waste.

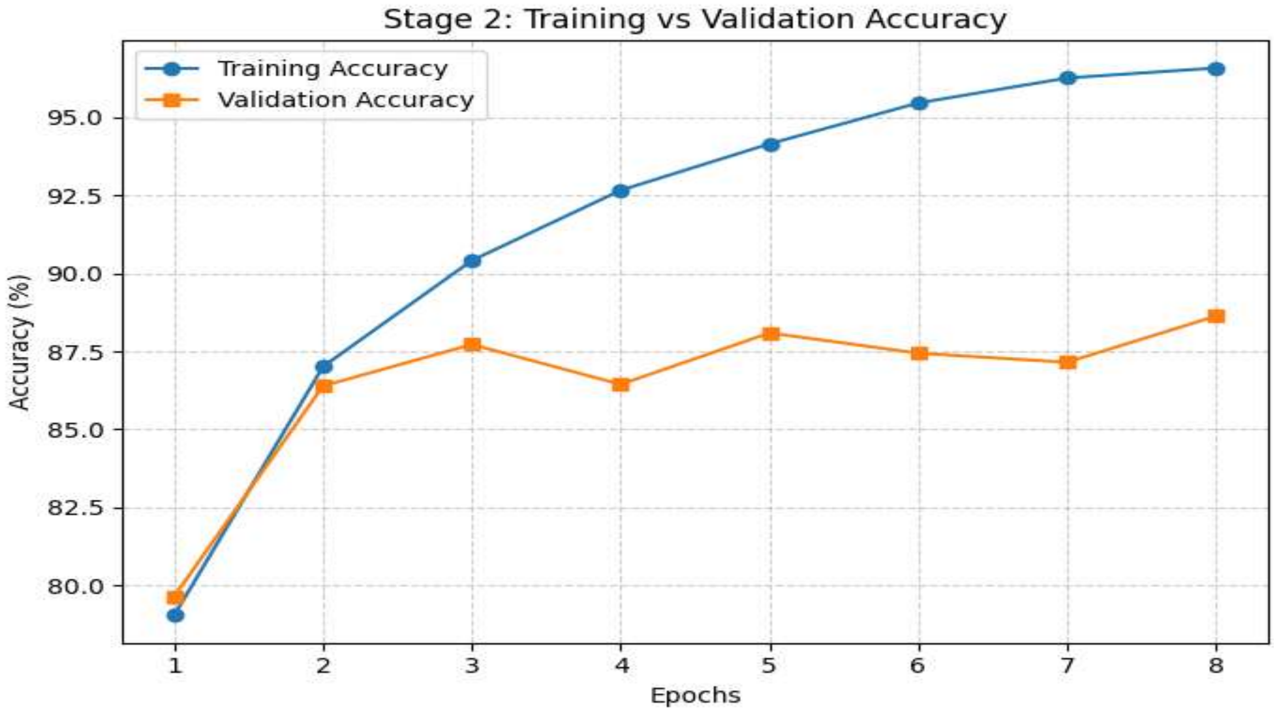

Figure 4.2: Training and validation accuracy across Stage 2

Stage 2 maintains high accuracy across nine material-level categories, indicating effective intermediate-level discrimination. Stage 3 exhibits comparatively lower accuracy due to increased class complexity and fine-grained categorization.

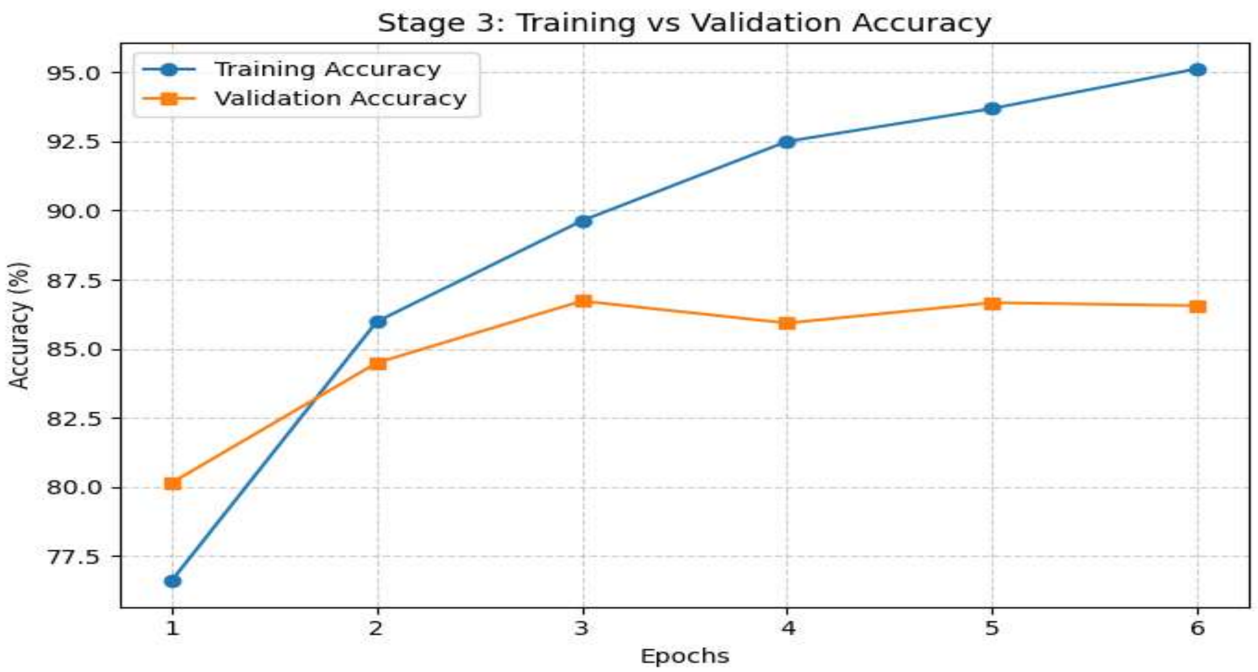

Figure 4.3: Training and validation accuracy acros Stage 3.

However, the hierarchical structure ensures stable convergence and reliable predictions, preventing drastic performance degradation as the number of classes increases.

4.2 Comparative Analysis

The comparative analysis highlights the effectiveness of the hierarchical approach in managing increasing classification complexity. While accuracy naturally decreases with finer granularity, the staged classification framework maintains acceptable performance levels and demonstrates better scalability than flat multi-class models.

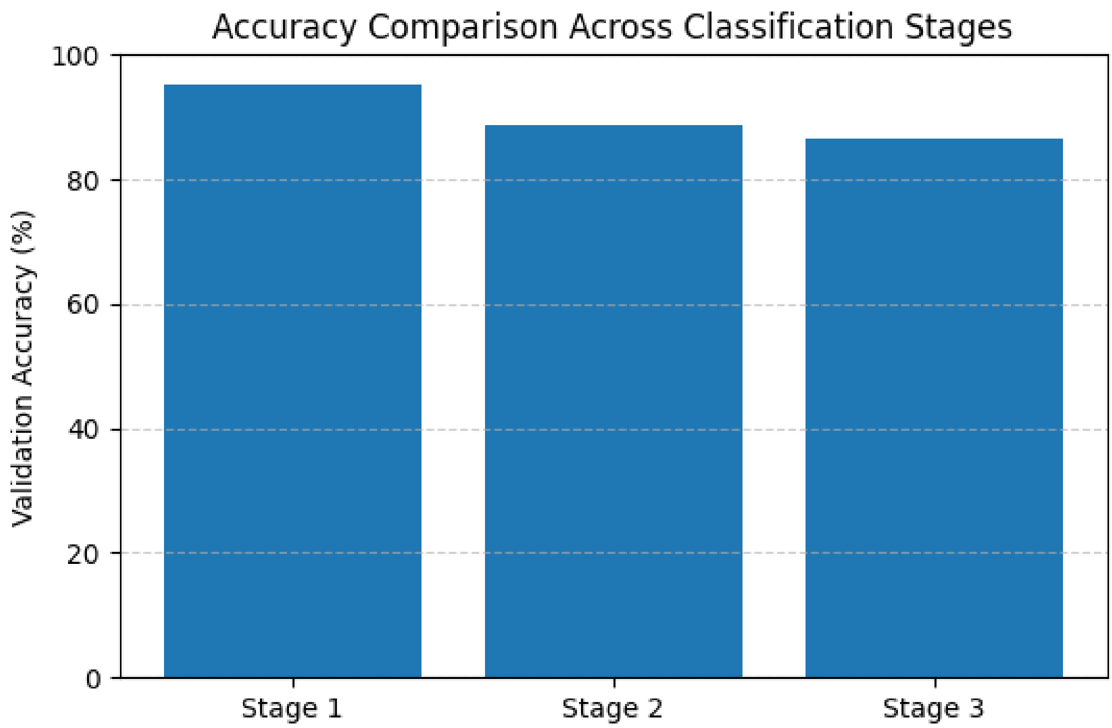

Figure 4.4: Comparative validation accuracy across all classification stages.

4.3 Sample Output Analysis

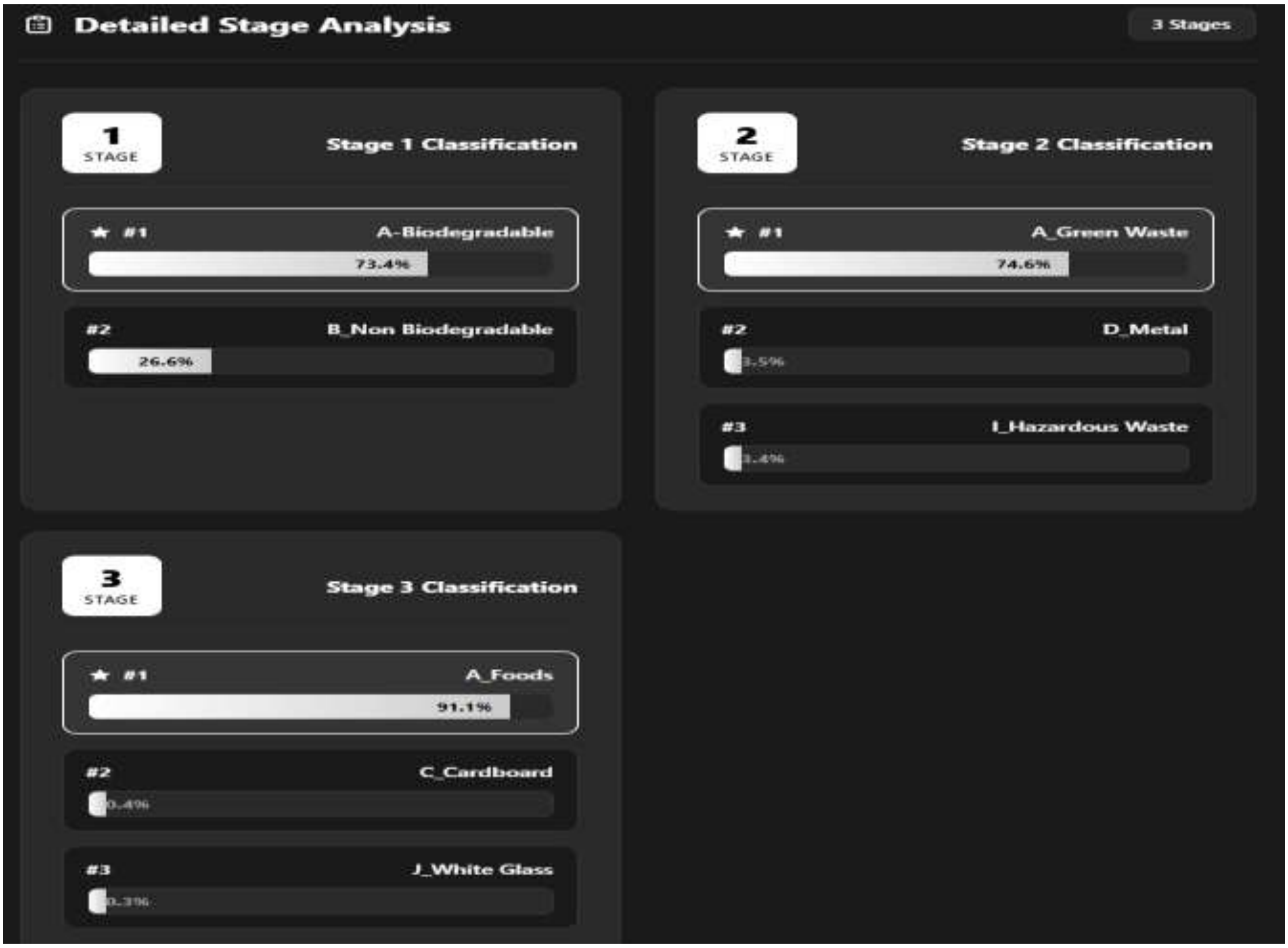

Figure 4.5: Sample hierarchical classification output generated by the system.

The sample output analysis illustrates the system's ability to provide stage-wise predictions along with confidence scores. Displaying intermediate results improves transparency and interpretability, enabling users to understand how the final classification decision is derived. This feature is particularly valuable in real-world applications where explainability is essential.

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