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Real-Time Hospital Waste Classification Using CNN-Based Smart Sorting System

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ABSTRACT

Effective classification of hospital wastes is important in minimizing the risk of infections, increasing hygiene, and ensuring adherence to healthcare waste management guidelines. This study presents the development of a real-time intelligent sorting system using Convolutional Neural Networks (CNNs) as a binary classification framework to classify hazardous and general waste in hospitals. Conducted in Pakistan, the study utilized a balanced dataset of 2,000 labelled waste images that were pre-processed by resizing, normalizing, and augmenting the images to improve model robustness. A small CNN network was built with TensorFlow and Keras and trained over 30 epochs, with accuracy and loss values used to validate the model. The model achieved the highest validation accuracy of 81.00% and the lowest validation loss of 0.43, showing good generalization ability. To make the trained model operational, it was incorporated with OpenCV and a normal webcam to classify waste products in real time, and live predictions of hazardous and general products received high confidence scores. The system was found to be responsive and computationally efficient; it does not require any GPU support and can be integrated into smart waste bin systems. This study contributes a scalable, low-cost technology to support hospital waste segregation, enhancing safety, automation, and environmental sustainability within healthcare facilities.

Keywords: Smart sorting, Convolutional Neural Networks, Hospital waste, Real-time classification, Deep learning

1. INTRODUCTION

Effective hospital waste management is not only a matter of hygiene but also a central operational and safety requirement. With growing patient volumes and the variety of waste streams, institutions require smart systems that can automate the classification process and reduce reliance on manual sorting. Deep learning provides a data-driven solution that enables the automatic identification and classification of waste items. This type of intervention significantly reduces human contact, thereby minimizing human error, strengthening compliance with regulatory principles of waste management, and reducing health risks to both medical staff and the community. The current paper examines how smart sorting through Convolutional Neural Networks (CNNs) helps build the resilience of hospital waste systems by accurately separating hazardous waste from general waste.

Hospital waste typically consists of biological and non-biological matter that cannot be reused, is normally classified into medical, domestic, and infectious waste [1]. Medical waste is generated during diagnosis and treatment activities, whereas infectious waste includes materials that can cause disease through contact with patients [2]. Syringes, surgical gloves, blood-stained bandages, and medicine containers are examples of hazardous waste [3]. Mishandling such materials increases the risk of infections and reduces operational efficiency. It is estimated that around 75–90 percent of hospital waste is equivalent to municipal waste, while

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about 10–25 percent is hazardous and can cause HIV, hepatitis B and C, and tuberculosis, among other pathogens, when mismanaged [4][5]. Therefore, unsafe waste management is estimated to cause millions of infections annually, particularly due to contaminated sharps and medical equipment, according to the World Health Organization (WHO) [6]. Improper segregation at the source level allows hazardous waste to mix with general waste, making handling processes more cumbersome and increasing both environmental and health risks [7, 8].

Traditional hospital waste sorting is based on manual visual inspection, which is a labour-intensive and time-consuming process that raises the likelihood of misclassification, potential cross-contamination, regulatory non-compliance, and exposure of healthcare staff and waste-processing workers [9]. Even in environments where colour coding of bins has been deployed, the accuracy of classification is affected by the regularity of staff adherence and the quality of individual decisions. The reliability of manual sorting is further compromised by emergency cases and peak clinical times, which in most cases lead to uneven waste-handling practices [10].

Recent advancements in artificial intelligence have introduced classification systems based on deep learning that can analyze the visual characteristics of waste images and identify their respective categories with a high level of precision. CNNs are characterized by high performance in image classification tasks and are being deployed in healthcare environments [11]. Although there have been past studies on the classification of waste using static image datasets, such systems have had limitations and failed to capture most of the dynamics of the hospital setting [12]. The current paper thus introduces a live-time smart-sorting system that uses CNNs to categorize hospital waste into two classes, hazardous and general, through a live webcam feed. A trained CNN model runs on each video frame, making video classification available in real time at the disposal point. This arrangement minimizes manual handling, increases the accuracy of segregation, and ensures handling safety as it facilitates immediate and uniform identification of hazardous material.

This study introduces a smart sorting system in real time using deep learning, which uses convolutional neural networks (CNNs) to perform binary classification of hospital waste. This method is selected for its demonstrated ability in visual features recognition, its minimal computational complexity, and its suitability for deployment in a hospital setting. The proposed model aims to enhance the efficiency of waste management, support regulatory compliance, and reduce the risk of exposure to biohazards by automating the waste-classification process. The research objectives include training and validating the CNN-based classification model, evaluating its effectiveness in reducing manual errors, and providing proof of its functional compatibility within a hospital setting.

The novelty of this study lies in the fact that a real-time classification system based on CNN is integrated, which processes live video data and enables immediate and automated classification of waste at the hospital. The approach provides a

scalable and practical solution with enhanced accuracy and reduced human interaction in hazardous waste management environments.

2. LITERATURE REVIEW

2.1 Convolutional Neural Network-Based Classification of Medical Waste in Real-Time Environments

Recent advancements in deep learning enabled the use of Convolutional Neural Networks (CNNs) applicable in the highly accurate classification of medical waste, especially in the dynamic healthcare setting. With this purpose, the current section reviews research that assesses real-time and static image-based classification systems aiming to facilitate hospital waste management through automation and artificial intelligence (AI) integration. Chan and Kim [13] developed a CNN-based system to classify waste, tailored for public engagement and environmental awareness in Malaysia. By combining primary and secondary waste image data, the researchers achieved a training accuracy of 80.66% and a validation accuracy of 77.62%. The use of a user-friendly web interface allowed users to capture or upload images and provided immediate results in waste classification, along with disposal guidelines. It was an initiative that helped promote Sustainable Development Goals (SDG 12 and 13) and aimed to increase the recycling rate of at least 40% by 2025 in Malaysia. Overall, the system provided an educational and practical solution to sustainably address waste management. Paneru et al. [14] proposed an intelligent waste management framework combining CNNs and IoT-based technology to perform real-time classification of organic and inorganic waste. A CNN model trained with a large dataset achieved a classification accuracy of 96%. The labelled waste data were sent to the cloud via the Blynk platform, while the dynamics of methane (CH₄) concentrations were tracked in real time using gas and ultrasonic sensors during ten days of continuous environmental monitoring, along with the evaluation of methane (CH₄) potential. The model successfully demonstrated how AI and IoT could be used together for sustainable and responsive waste management. Kumar et al. [15] designed a hybrid deep-learning model based on the combination of the Convolutional Neural Network (CNN) and the Gated Recurrent Unit (GRU), with the addition of transfer learning to increase the accuracy of waste classification. The CNN was used to capture spatial characteristics, and the GRU was used to process sequences in time, while the model reused the parameters of a network trained previously. Tested on a public waste dataset, the hybrid model had a 97% accuracy in classification, which was better than existing conventional CNNs and Long Short-Term Memory (LSTM) baselines. With the use of Python, the research proved that joint spatial-temporal modelling was capable of significantly increasing the accuracy of classification, which supported the validity of hybrid deep-learning approaches to sustainable AI-based waste-management systems. Ahmed and Shanto [16] conducted a comparative analysis of three variants of the You Only Look Once (YOLO) detector, i.e., YOLOv5, YOLOv7, and YOLOv8-m, in medical waste detection (over the MSG dataset). In their findings, they reported that YOLOv8-m achieved the best mean average precision (mAP), with a mAP of 82.4% reported. They

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implemented a uniform training protocol to ensure a fair evaluation across versions. The results revealed the improvement in object detection accuracy with newer YOLO variants. Their work set a benchmark for precision in AI-assisted classification of hazardous surgical waste. Van den Broek et al. [17] developed a hybrid deep-learning model that combined Capsule Networks and DenseNet to identify medical waste. The system achieved this by incorporating two features, spatial-relationship encoding and deep-feature extraction, to enhance the reliability of classification, which increased the F1-score from 0.89 to 0.92. The system was trained and tested on static pictures; the method demonstrated increased sensitivity to various types of waste and highlighted the benefits of integrating feature extraction and spatial awareness into a single architecture. This approach marked a significant step toward building more context-aware hospital waste classification models. Bruno et al. [18] developed an offline medical waste sorting model using deep learning techniques for static image classification. Their computer vision system achieved 100% accuracy on a curated and well-labelled dataset, demonstrating that CNNs can perform near-perfect classification with high-quality data. The model supported rapid processing and did not require the use of a network connection due to its offline design, but it was not real-time. However, the findings confirmed that deep learning could be effectively used as a solution to automated sorting in hospitals and justified the implementation of highly precise offline AI in scenarios of waste management. Gan et al. [19] built an embedded system based on CNN and used GoogLeNet to classify medical waste: general infection, dangerous infection, and general garbage. They developed both hardware and software modules, used 2,025 self-collected images, and performed image processing to classify them. The system achieved a best-case accuracy of 99.34 % and was able to operate autonomously, i.e., using visual input, the system activated sorting bins. They focused on the safety and automation of healthcare waste in their architecture, especially during a pandemic where medical waste surges increased handling risks. Hermawan et al. [20] developed a hazardous classification system for medical waste by using YOLOv5 on a Raspberry Pi. The system aimed to address the inefficiency that existed in previous approaches based on CNN and Single Shot MultiBox Detector (SSD), which had low accuracy and high latency. Their implementation of YOLOv5 achieved classification accuracy of 85 % and 96 % at various image resolutions (128 x 128 and 25 x 320 pixels) using less than 5 seconds. The framework provided an efficient and low-cost real-time detection system to manage pandemic-related biomedical waste. Kabilan et al. [21] proposed an automated CNN-based waste classification system for smart cities, categorizing waste into biodegradable, non-biodegradable, biomedical, and electronic types. The combination of their CNN model with data augmentation and noise removal made the model very accurate at 91.87 %, and it outperformed traditional machine learning models like Support Vector Machine (SVM) and Random Forest. The model architecture that is proposed has carefully designed convolutional, pooling, and dense layers. The system is intended to be used on edge devices and can provide real-time classification with minimum reliance on central processing, which makes it relevant to healthcare and smart-industry settings.

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Unlike previous studies that focused either on real-time classification via IoT or hybrid deep models, the proposed paper develops a lightweight, yet effective CNN-based system tailored specifically for hospital waste sorting using static images. While several works utilized advanced architectures like YOLO or hybrid CNN-GRU frameworks, they emphasized general or surgical waste and often lacked deployment simplicity. This paper uniquely focuses on hazardous vs general classification using a balanced dataset of labelled hospital waste images, enabling high-accuracy sorting with minimal hardware requirements. Additionally, it supports both static and webcam input, offering deployment flexibility in hospital settings. The system is designed for integration at source-level sorting stations, prioritizing hygiene, automation, and minimal human contact. Thus, it addresses a practical, safety-focused gap not directly tackled in the reviewed literature.

2.2 Live Video-Based General Waste Detection and Transferable CNN Applications

The development of waste management to intelligent and automated systems has led to an increased dependence on convolutional neural networks (CNNs) in the form of live video analysis and waste-specific tasks. The selected studies demonstrate the effectiveness of the flexibility of CNN architectures and hybrid system design to maximize performance in detection and enable scalable real-world deployment. Vo et al. [22] introduced a real-time trash classification system using AIoT that was based on the RegNetY120 backbone. Their implementation of CNN, which they named BEGNet, functioned on smart camera-based hardware and categorized waste based on live video feed and directed end users on optimal waste disposal practices. Both experiments on the TrashNet dataset and a custom dataset demonstrated better results than baseline models and attained improvements in accuracy at low computational costs. By focusing on the low-cost integration of smart waste bins and by raising awareness among citizens, the study proved the feasibility of integrating AI models and physical devices to solve real-world waste classification challenges. Mehadjbia and Hasnaoui [23] used the YOLOv8 model on live video streams to categorize eight classes of general waste with a mean average precision of 78% and a precision score of 73% under diverse real-world conditions. The system performed well in various settings such as hospitals, public areas, and clinics, and was able to process live camera feeds, thus proving to be suitable for rapid and responsive waste categorization. The results emphasized the significance of real-time applications of CNN in waste management within dynamic disposal environments. Matsnan Haqqi et al. [24] developed a convolutional neural network (CNN) in which the goal was to classify six waste types, namely glass, paper, cardboard, plastic, organic, and metal, on a dataset with 2,848 images. Pre-processing was done by reducing noise through filtering operations, smoothness through a Gaussian kernel and cropping of the image. The trained model was tested on 57 epochs and learning rate 0.0001 which achieved 95.64 % accuracy and a minimum loss of 0.3806. The results of the analysis showed stable performance in F1 scores and confusion matrix indicating that the system is performing well in detecting all types of waste. Finally, the results have proven that CNN-based

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paradigms achieve high classification rates and can be deployed to large-scale implementations, thus, breaking the state of the art in waste management. Uluturk et al. [25] conducted extensive research on a pool of convolutional neural network (CNN) models, including VGG19, DenseNet169, ResNet101, InceptionV3, and EfficientNetV2S, for the classification of waste. They used Transfer learning, hyperparameter training (via GridSearch), and the comparison of pre-trained and simple models was conducted. They affirmed that DenseNet169 provided the most stable performance with an accuracy of 96.42% and an F1 score of 96%. The results suggested that CNN models, and specifically DenseNet169, had better generalization in large image-based sorting and even proved the argument of CNN-driven automated waste-sorting systems. Aluvalu Reddy et al. [26] proposed a smart waste classification model that used AI and integrated the VGG16 architecture for sorting plastic, glass, metal, organic, and dangerous streams of waste. The system was integrated with IoT for real-time monitoring and data collection, improving sorting precision and recycling efficiency. The training used data up to October 2023, with preprocessing to standardize inputs and enhance model robustness. Their framework emphasized urban waste sustainability by minimizing landfill reliance and supporting automated waste tracking. The model's integration into smart city applications demonstrated strong environmental and cost-saving potential.

While prior studies explored live video-based CNNs and hybrid models for general or industrial waste, the proposed paper addresses hospital-specific waste classification using static images, which remains underexplored. Unlike real-time systems requiring continuous video processing or complex transformer-based designs, this work offers a deployable image-based CNN model with webcam support, enabling scalable sorting without high-end hardware. It focuses on binary classification (hazardous vs general) using a clean, balanced dataset tailored to hospital conditions. The model's simplicity ensures ease of implementation at hospital sorting stations while maintaining reliable accuracy. Thus, it provides a practical, healthcare-specific solution that is absent in general-purpose or industrial waste models reviewed.

Table 1: Comparative Summary of CNN-Based Waste Classification Studies

Authors	Year	Model Type	Input Type	Waste Type	Classification Type	Deployment Mode	Quantitative Results	Frameworks Used	Country
Bruno et al. [18]	2023	CNN	Static Images	Medical	Multi-class	Offline	100% accuracy	Custom dataset, CV tools	Pakistan
Uluturk et al. [25]	2023	DenseNet169 (CNN)	Static Images	General	Multi-class	Offline	96.42% accuracy, 96% F1	Transfer Learning	Turkey
Hermawan et al. [20]	2023	YOLOv5	Live Camera (Raspberry Pi)	Medical	Multi-class	Real-time	85%-96% accuracy	YOLOv5, Raspberry Pi	Indonesia

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Chan & Kim [13]	2024	CNN	Static + Uploaded Images	General	Multi-class	Real-time (Web-based)	80.66% training, 77.62% validation	Web interface, SDG support	Malaysia
Paneru et al. [14]	2024	CNN + IoT	Static + Gas/Ultrasonic Sensors	General	Binary	Real-time	96% accuracy	Blynk, Cloud, IoT	Nepal
Kabilan et al. [21]	2024	CNN	Static Images	General + Biomedical	Multi-class	Real-time (Edge)	91.87% accuracy	Edge-optimized CNN	India
Ahmed & Shanto [16]	2024	YOLOv5/v7/v8-m	Static Images	Surgical	Multi-class	Offline	YOLOv8-m: 82.4% mAP	MSG Dataset	Bangladesh
Vo et al. [22]	2024	BEGNet (CNN)	Live Video	General	Multi-class	Real-time	Outperformed baseline models	RegNetY120, TrashNet	Vietnam
Mehadjbia & Hasnaoui [23]	2024	YOLOv8	Live Video	General	Multi-class	Real-time	78% mAP, 73% precision	YOLOv8, Live detection	Algeria
Gan et al. [19]	2024	GoogLeNet (CNN)	Static Images	Medical	Multi-class	Autonomous sorting	99.34% accuracy	CNN, Hardware integration	China
Matsnan Haqqi et al. [24]	2024	CNN	Static Images	General	Multi-class	Offline	95.64% accuracy, 0.3806 loss	Gaussian filtering, F1 matrix	Indonesia
Kumar et al. [15]	2024	CNN + GRU	Static Images	General	Multi-class	Offline	97% accuracy	Transfer learning, GRU	India/ UAE
Van den Broek et al. [17]	2025	CapsuleNet + DenseNet	Static Images	Medical	Multi-class	Offline	F1-score: 0.92	Hybrid DL model	Netherlands/Iran
Aluvalu Reddy et al. [26]	2025	VGG16 (CNN)	Static Images	General + Hazardous	Multi-class	Real-time (IoT)	High accuracy (value not given)	IoT + Smart city tools	India
Proposed Study	2025	Lightweight CNN	Live Webcam	Medical	Binary	Real-time	81% accuracy, 0.43 loss	TensorFlow, Keras, OpenCV	Pakistan

3. METHODOLOGY

3.1 Research Design and Framework

In this paper, the applied experimental research design was used in developing and testing a real-time hospital waste classification system by applying Convolutional Neural Networks (CNNs). A supervised learning model was used, and the model was trained on a labelled dataset of 2,000 images, which were in a 50:50 ratio between the hazardous and general waste classes. The methodology was categorized as systematic: it began with loading and pre-processing of the dataset,

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and then the dataset was resized to match the size of each image (128 x 128 pixels), the values of pixels were normalized, and augmentation techniques (to enhance generalization) like flipping and zooming were applied. Then, a CNN model with 4 layers and ReLU activations, as well as a max-pooling layer, was constructed, and a dense final layer and a sigmoid output were added to obtain a binary classification.

Binary cross-entropy loss and RMSprop optimizer were used in the creation of the model, after which the model was trained for 30 epochs, with a batch size of 32, and with validation monitoring. The values used were chosen by experiment to have a compromise between computing and performance. The use of 32 as the batch size enabled the training to remain stable, and recurring error messages were eliminated using this batch size without an increase in the training time. The use of increasing values resulted in more time-consuming training with no significant enhancement in the accuracy of the training. In a similar way, validation accuracy gradually increased until 30 epochs, and then the results became marginal, and risks of overfitting occurred. A decision checkpoint was used to monitor model performance during training so that parameter tuning could be done if validation accuracy was low. After achieving satisfactory performance, the model was saved, and a real-time video classification system was implemented with the help of OpenCV. The trained model used to classify the frames taken by a webcam was accurate and resized each frame, wrote the result on-screen with the help of the bounding boxes, labels, and a confidence score. The system ran and processed frames until it was stopped by hand. An explanation of this end-to-end process was shown in Figure 1, which was a generalized recounting of the methodology from dataset preparation to the live deployment of the method.

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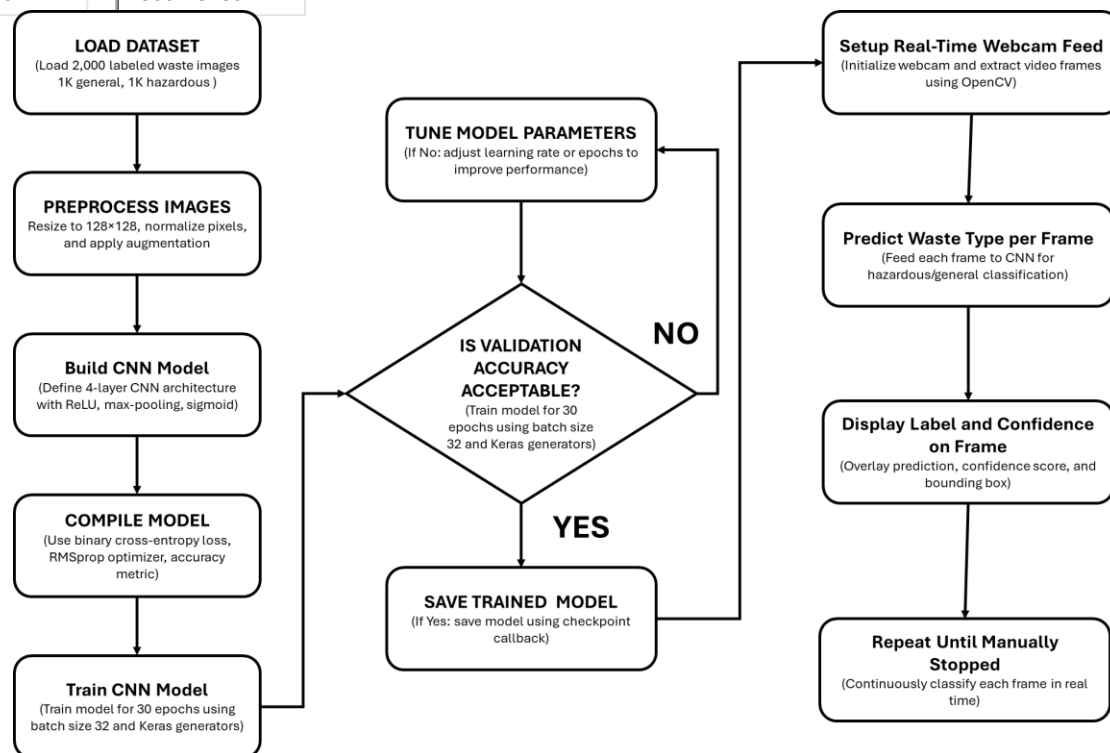
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Figure 1: Methodology Flowchart for CNN-Based Smart Sorting System

3.2 Study Context and Data Source

3.2.1 Dataset Composition and Source

The dataset of the images in this study was obtained from Kaggle, with 2000 labelled images having an even distribution between hazardous and general hospital waste, as illustrated in Figures 2 and 3. Examples of the medical waste included used syringes, soiled gloves, bandages, and items used in the packaging of medicine that were known to contain contamination risks. Sample general waste included such items as paper sheets, plastic wrap, bottles, and single-use food containers that were typically produced in non-clinical hospital spaces, cafeterias, and offices.

3.2.2 Image Diversity and Relevance

The selection of each of the pictures was subject to variation in background and lighting to provide greater generalization in training. This was done to develop a model that could have the ability to identify waste items in various visual conditions, an imitation of the variability experienced in real hospital disposal situations. The balance between the two waste categories in the dataset provided a good base to train a CNN model that could be deployed using binary classification, and the diversity of the images provided resilience in deployment.

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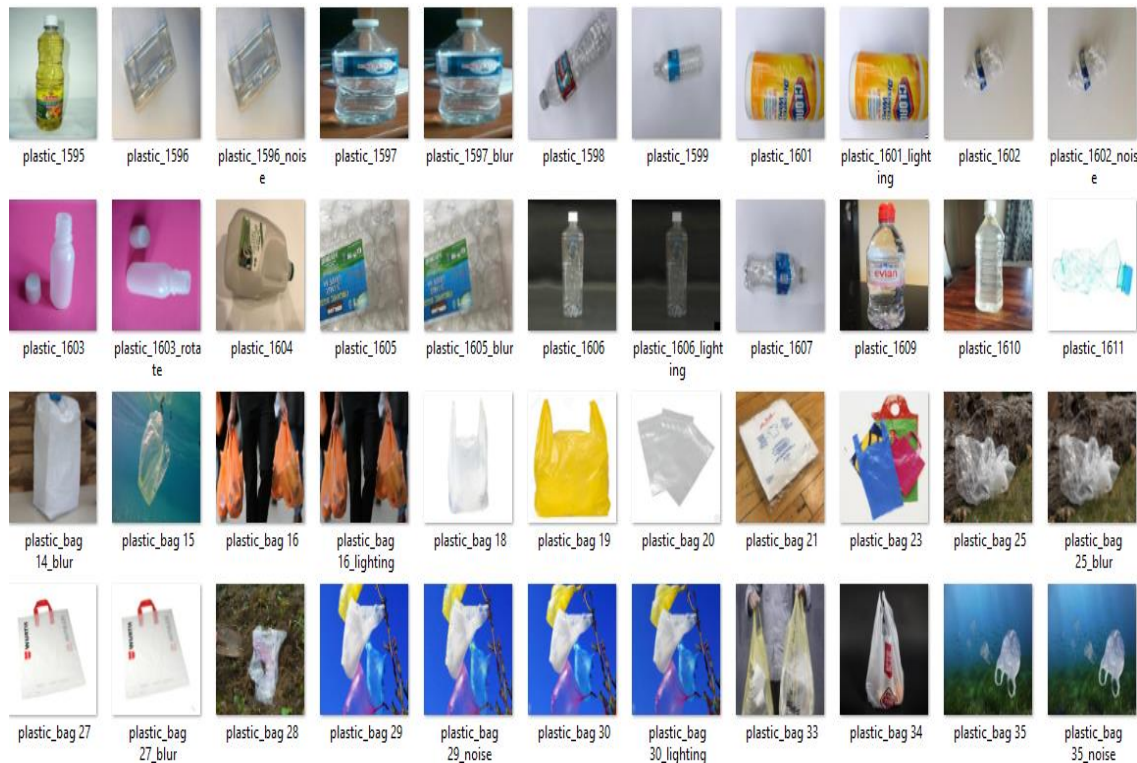


Figure 2: General waste

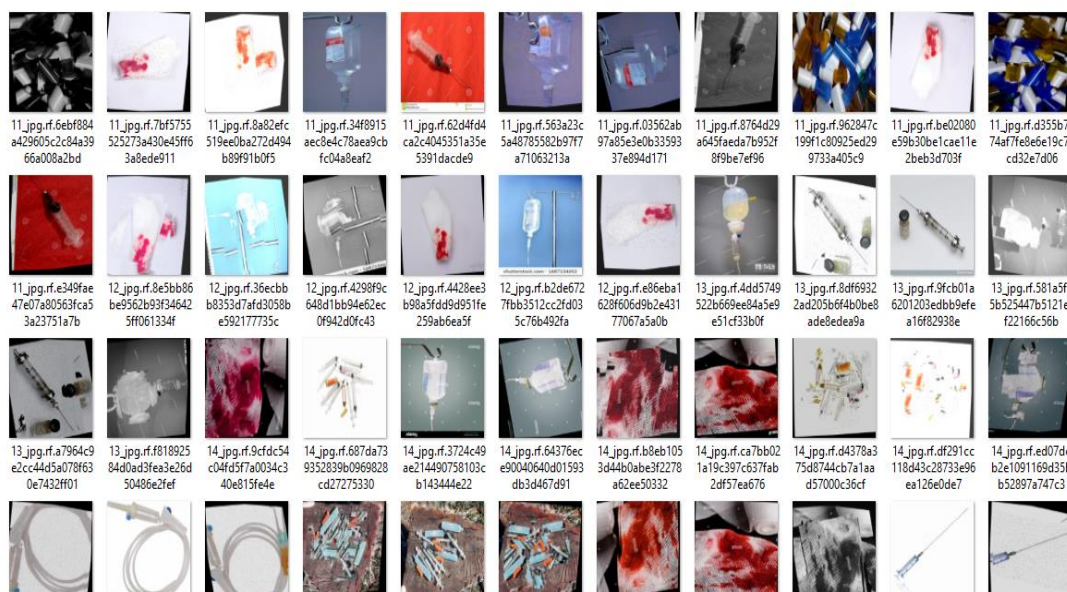


Figure 3: Healthcare Hazardous Waste

3.3 Data Preprocessing and Augmentation

3.3.1 Image Standardization

To ensure consistency in input shape, all images were resized to 128×128 pixels as shown in Figure 2 and 3. This resolution was selected based on the computational efficiency and compatibility with the CNN input layer. Pixel values were normalized to a range between 0 and 1 to accelerate convergence and maintain training stability. These standardization steps were essential for minimizing bias introduced by size or intensity variation across the image dataset.

3.3.2 Augmentation and Input Pipeline

Data augmentation was applied using the ImageDataGenerator module from Keras, which supported real-time data loading and transformation. The augmentation included horizontal flipping and zoom operations, designed to simulate natural variations in waste presentation. These transformations enhanced the model's ability to generalize by exposing it to altered perspectives and distortions of the same objects. Augmentation also contributed to minimizing overfitting by diversifying the training samples while preserving label integrity. The entire preprocessing pipeline enabled an optimized and robust data flow for training the CNN model.

3.4 CNN Model Architecture

The architecture of the models had a sequential CNN type and was implemented using TensorFlow and Keras. It had four convolutional layers with the ReLU activation function and a max-pooling layer after every convolutional layer. These gradually depleted the spatial context size of the feature maps and avoided losing essential visual characteristics, applicable to classifying the wastes. After the convolutional blocks, the dense layer with 50 neurons was used, and the output was flattened. The last layer of classification was the single neuron that had the sigmoid activation utilized in anticipating the affiliation of the input in the profane waste class or the general waste class. Dropout layers were avoided because the size of the dataset was moderate and the distribution of the classes was equal, which lowered the chances of overfitting. The model architecture was lightweight and thus fit well in being implemented as a real-time inference with minimal latency using conventional computing equipment. The entire architecture, the number of available neurons, and the flow of operations could be seen in Figure 4.

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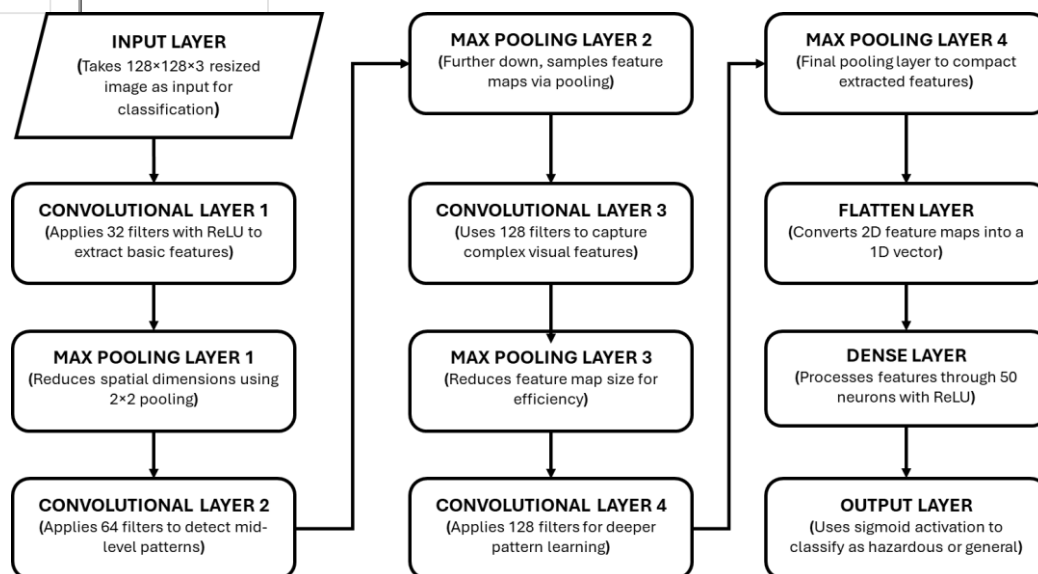


Figure 4: Flowchart of CNN Model Architecture for Smart Waste Classification

3.5 Model Compilation and Training Parameters

3.5.1 Compilation Settings

Once the CNN architecture was finalized, the model was compiled using binary cross-entropy as the loss function, which is suitable for binary classification problems. RMSprop was chosen as the optimizer with a learning rate of 0.0001, allowing for gradual updates that help maintain training stability. Accuracy was used as the primary evaluation metric to monitor the model's learning progress and effectiveness during training.

3.5.2 Training Configuration

The training process was carried out over 30 epochs with a batch size of 32. The dataset was split into training and validation subsets to assess generalization. Keras data generators made it easy to feed the images during the training cycle to keep constant inflow. An automatic model backup was implemented in the form of a checkpoint callback that would save the most successful version of the model according to the validation loss. This made sure that the developed last implemented model was streamlined in accuracy and reliability. The model also exhibited an increasingly high validation performance during training, with its trajectory being stable, and it passed the test of suitability to be deployed.

3.6 Performance Visualization

The evaluation of the performance of the model was based on the visual inspection of the training metrics over epochs. Matplotlib was used to plot the accuracy of correlated programming and loss on training and validation sets to have a clear display of learning behavior. With the use of such plots, convergence trends could be identified, as well as potential overfitting or training instability. The generalization of the model to unseen data is a sign of this because an increasing validation accuracy and a decreasing validation loss were obtained. The

visualization helped in the explanation of the model and evidence-based selection of the model in real-time. These insights were instrumental in confirming training effectiveness and the model's readiness for operational deployment.

3.7 Real-Time Deployment and System Integration

3.7.1 Frame Processing and Classification Workflow

The CNN model was then implemented in a video classification setting in real-time with the help of OpenCV after being trained. An ordinary webcam was used to imitate real circumstances of waste disposal within a hospital. Every video frame captured was reduced to 128x128 pixels and normalized to meet the specifications of the trained model as input.

The model was trained to classify the content as either hazardous or general waste after receiving a processed frame. It thereafter presented the result of the classification by superimposing the label and confidence score over the video feed. Red labels signified hazardous waste, and a green label was a sign denoting general waste. This real-time visual feedback made it simple to identify at the point of disposal and provided a pseudo smart bin interface in a real-time hospital scenario.

3.7.2 Real-Time System Functionality

The classification system was in a closed-loop operation, a single frame being processed in real-time until the application was shut down manually. The detected area where the object was drawn was enclosed in a bounding box as a way of highlighting the point of disposal. Such an implementation proved the real-time responsiveness of the model and demonstrated that the light CNN architecture could complete low-latency predictions appropriate to be applied in an intelligent waste-sorting system in the healthcare environment.

3.8 Hardware and Software Environment

The developed system was based on Python and ran on a Windows machine that lacked GPU acceleration. TensorFlow and Keras were also used in various model development, training, and deployment of the developed neural networks. OpenCV was also incorporated to perform real-time video database handling and processing of frames. Preprocessing and augmentation of images were conducted with the help of Keras ImageDataGenerator, while Matplotlib and Seaborn were used to visualize and report results. In the main, the development work was done in Jupyter Notebook. A regular USB webcam was applied in the testing procedures to simulate live classification situations. Both the hardware and software selection were undertaken to ensure compatibility, efficiency, and the ease of installation within the non-specialized systems that were used in healthcare facilities.

4. RESULT AND DISCUSSION

4.1 Epoch-wise Training and Validation Performance

The CNN model demonstrated consistent learning progress throughout the 30 training epochs. It began with modest performance, achieving 56% training accuracy and 52% validation accuracy in the first epoch, along with a high

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validation loss of 0.682. However, with continued training, both metrics improved significantly. By epoch 19, the model achieved 77.5% validation accuracy, and the validation loss dropped to 0.479. The best overall performance was recorded at Epoch 28, where the model reached 81% validation accuracy and the lowest validation loss of 0.434. The training accuracy was also maintained over 85 percent in the subsequent phases, which signified that there was a good learning and generalizing capacities. Despite some irregularities in terms of validation loss after some epochs, the model had no signs of overfitting, and the model converged well. These results indicated that CNN was capable of effectively differentiating between hazardous and general waste types. On the whole, the model has shown good results and can be deemed as appropriate to use in real-time applicability to waste classification in hospitals, especially the good rate of accuracy and the responsiveness in its behavior throughout the validation.

Table 2: Epoch-wise Training and Validation Performance of CNN Model

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	56.00%	0.6851	52.25%	0.6826
2	62.50%	0.6519	54.75%	0.6803
3	65.94%	0.6457	63.00%	0.6670
4	90.62%	0.5210	59.00%	0.6655
5	70.20%	0.6025	55.00%	0.7853
6	59.38%	0.6084	64.00%	0.6710
7	74.20%	0.5682	64.50%	0.6374
8	71.88%	0.5240	64.00%	0.6929
9	78.30%	0.5224	66.00%	0.6753
10	78.12%	0.4793	67.25%	0.6005
11	79.46%	0.4759	71.50%	0.5893
12	78.12%	0.5650	69.25%	0.6546
13	81.34%	0.4537	72.75%	0.5624
14	100.00%	0.2371	72.75%	0.5723
15	82.50%	0.4072	73.50%	0.5229
16	87.50%	0.3168	73.75%	0.5423
17	83.93%	0.3807	74.25%	0.5312

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18	93.75%	0.3561	73.75%	0.5711
19	85.91%	0.3673	77.50%	0.4794
20	90.62%	0.2887	75.25%	0.5120
21	85.89%	0.3378	71.50%	0.6066
22	84.38%	0.4019	72.50%	0.5634
23	85.58%	0.3569	76.25%	0.4982
24	93.75%	0.1799	77.50%	0.4767
25	86.04%	0.3465	79.50%	0.4545
26	96.88%	0.1939	78.25%	0.4745
27	86.98%	0.3263	80.25%	0.4561
28	96.88%	0.1558	81.00%	0.4348
29	86.97%	0.3202	77.25%	0.5007
30	100.00%	0.2254	80.50%	0.4505

4.2 Accuracy Analysis:

The graph of training accuracy and validation accuracy shows the behavior of learning with the CNN model after 30 epochs. Originally, the training performance was approximately 56%, whereas validation performance began at a little more than 50%. The progress made on the two metrics improved steadily as training progressed, which implies that the learning and generalization occurred effectively. In the mid-epochs, the model passed the mark of 80% accuracy in training, and the validation accuracy rose steadily to the highest point at 81% around the 28th epoch. Training accuracy was as high as 100% in the last Epochs, whereas validation accuracy showed slight variations but still in a stable form, which may indicate controlled overfitting. The difference between the two curves results in a moderate result, which indicates the strength and the stability of the model. Overall, the accuracy trend confirms that CNN successfully learned to distinguish hazards from general waste with high reliability.

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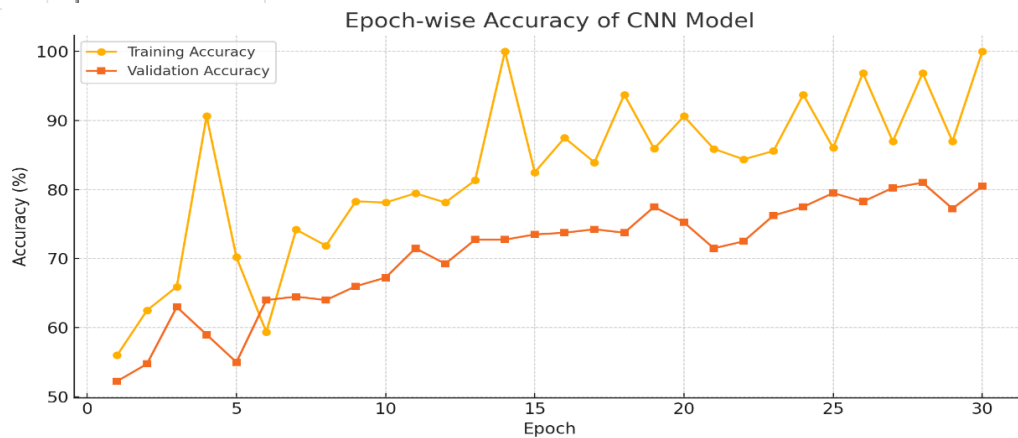


Figure 5: Epoch-wise Accuracy of CNN Model

4.3 Loss Analysis

The training and validation loss graph shows that there is a downward trend as the training epochs increase to 30. Training and validation losses initially had a value of approximately 0.68 and 0.75, indicating that the model had trouble differentiating between the two waste types. The training loss also decreased steadily as the training continued, with the lowest observed value being 0.15, which was evidence of good model learning. The validation loss, although more fluctuating, followed a general decline and reached its lowest point at approximately 0.43 near epoch 28. These fluctuations are typical when working with relatively small datasets, yet the absence of sharp divergence between the curves suggests minimal overfitting. The consistent gap between training and validation losses highlights the model's ability to generalize well on unseen data. Overall, the loss graph confirms stable convergence and supports the reliability of the model in real-world classification scenarios.

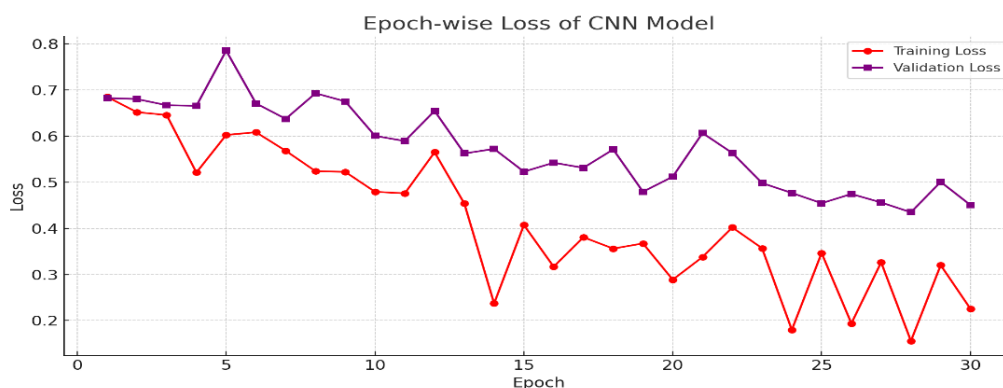


Figure 6: Epoch-wise Loss of CNN Model

4.4 Real-Time Classification Results

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The model was also tested on real-time classification with the webcam input being real-time. The system was able to identify the waste items generically and with a high degree of confidence to be considered as either hazardous or general. As displayed in Figure 8, the usage of a syringe was successfully identified as hazardous (0.89), having a strong confidence score, showing the ability of the model to identify the risk of using medical goods. Likewise, the items of general waste, including folded paper and plastic bottles, were correctly identified as general, with confidence scores of 0.70 and 0.69, respectively, as it was identified in Figure 7. The graphical representation, such as colour tags, meant that there was no difficulty in interpreting the stratification straight away. These findings supported the model to be responsive and reliable in dynamic environments and showed that it could be integrated into bright bin systems within hospital environment settings. The correct categorization of different waste items reflected the stability of the model beyond the process of image testing.

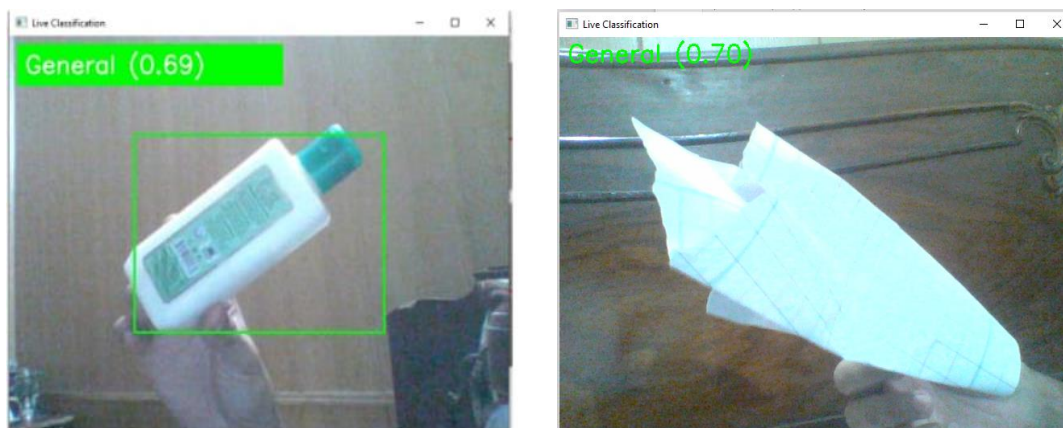


Figure 7: Classification of General Waste with confidence score

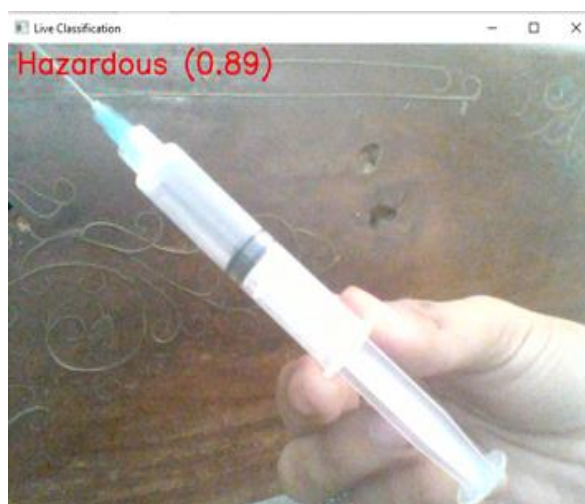


Figure 8: Classification of Hazardous Waste with confidence score

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4.5 Discussion of Findings

In this study, the results proved the suitability and effectiveness of Convolutional Neural Networks (CNNs) in real-time classification of hospital waste as hazardous and general. The presented model generalized to unseen data during the evolution of over 30 epochs on a balanced dataset containing 2000 images and reached a maximum validation accuracy of 81.00% and a minimum validation loss of 0.43, which proved successful learning and generalization. With stable convergence, the training accuracy was 100%, and there was no chance of overfitting. The effective implementation of the model was shown in real-time classification trials with the input of a webcam. The model detected several types of hazardous waste and general waste at a confidence level, with particular substances being syringes with a confidence score of 0.89, paper and plastic bottles with confidence scores of 0.70 and 0.69, respectively. These outcomes maintained the strength and agility of the model in the working environment. It was also characterized by its binary nature, lightweight architecture, and compatibility with other standard hardware, which made it an ideal and scalable solution in a hospital setting where technical and resource limits were usual.

As another criterion to judge its feasibility, the proposed system was contrasted with other recent CNN-based models that had been applied in waste classification. The table below explains how accuracy and efficiency were balanced in the given approach, and that the training requirements and hardware simplicity remained at low levels.

Table 3: Comparative Analysis of CNN-Based Waste Classification Models of Studies

Author(s)	Year	Model	Epochs	Accuracy	Waste Type	Remarks
Ulutürk & Kaya [25]	2023	DenseNet169 (CNN)	50	96.42%	General Waste	Transfer Learning
Matsnan Haqqi et al. [24]	2024	CNN	60	95.64%	General Waste	Standard CNN Architecture
Bruno et al. [18]	2023	CNN	50	100%	Medical Waste	Offline Static Classification
Kabilan et al. [21]	2024	CNN	100	91.87%	Biomedical + General Waste	Edge-Optimized Architecture
Proposed Study	2025	Lightweight CNN	30	81.00%	Hospital Medical Waste	Real-Time Webcam Input

This comparison highlights that while models like those by Ulutürk and Kaya [25] and Matsnan Haqqi et al. [24] achieved high accuracy (96.42% and 95.64% respectively), they required 50–60 training epochs and relied on more complex CNN architectures or transfer learning. Similarly, Bruno et al. [18] and Kabilan et al. [21] reported 100% accuracy with a simple CNN and 91.87% with 100 epochs; however, they all

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worked in optimized or edge-based conditions and would be inapplicable in a real-life hospital scenario. On the contrary, the suggested model delivered an accuracy of 81.00% using a light CNN with just 30 epochs, ordinary equipment, and no GPU or sensor augmentation. This confirmed the practicality and efficiency of the model, particularly in a setting where simplicity, cost-effectiveness, and real-time performance were expected.

5. CONCLUSION

The study generated and tested the concept of a smart sorting system to determine hospital waste by utilizing Convolutional Neural Networks (CNNs). Image-based learning and real-time video inference in the system were used to ensure that hazardous and general waste could be differentiated. The pre-processing of the data consisted of resizing, normalization, and augmentation to provide the model with the ability to handle multiple lighting and background situations. This was done using a set of 2,000 labelled images. CNN enabled by TensorFlow and Keras had four convolutional layers capped by matched dense and sigmoid-activated output layers with a suitable result of binary classification. The model was trained on a minimum of 30 epochs, and the highest validation accuracy that was reached was 81.00%, while the lowest validation loss achieved was 0.43, and there was no sign of overfitting. The model was deployed in real-time in an OpenCV-based system that utilized a webcam as input, with confidence scores that showed satisfactory applicability, as it was able to classify, with 100 percent accuracy, items such as syringes, paper, and plastic bottles with confidence scores of 0.69 and higher.

The proposed system produced not only consistent results in training and validation but also rendered real-time classification with an extremely low computing requirement. The ease of functioning on a normal machine, which does not have GPU support, is possible through its hardware-friendly design, which makes it affordable to a diverse set of healthcare facilities, even in areas that lack serious technological support. The system improves the safety and hygiene of operations, reduces reliance on the manual sorting process, eliminates chances of contact with infectious materials, and ensures adherence to regulations of biomedical waste disposal. Connected to smart waste bins or disposal units, this is a viable channel for automating source segregation, which can be a starting point of errors in managing medical waste. It is also a practice that ensures transparency and traceability in hospital waste flows, which are essential in environmental audits and risk assessments in healthcare.

Beyond its technical contribution, this work supports broader healthcare and environmental ambitions through its coverage of major areas of engagement in the Sustainable Development Goals (SDG 3: Good Health and Well-being, and SDG 12: Responsible Consumption and Production). The real-time success of the model in image classification provides an opportunity to advance toward future improvements in multi-class waste classification, robotics collection systems, and embedded and mobile applications. Moreover, there is a possibility for the methodology to be transferred to other areas like industrial sorting, food waste management, or city sanitation infrastructure. The study shows that DL-based visual classification can be transferred to

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large-scale solutions beyond its conventional application in laboratory testing and can be applied to address some of the challenges of practical waste management in hospitals and other such crucial sectors.

6. FUTURE WORK

The proposed research was able to use Convolutional Neural Networks (CNNs) and apply the technology in order to classify hospital waste into hazardous and general types with the help of image-based input and live video feed in real time. The system implemented in Python, TensorFlow, Keras, and OpenCV was able to come up with impressive accuracy and responsiveness with its lightweight and hardware-friendly state. The following are the suggestions for further improving the performance, scalability, and applicability of this system. Adoption of the strategies can considerably improve such possibilities of the model and promote its progress towards its deployment in real-life healthcare settings:

- **Expand to Multi-Class Waste Categorization:** Introduce additional waste categories such as sharps, recyclable materials, pharmaceuticals, or radioactive items to move beyond binary classification. This will improve the granularity of sorting and align the system more closely with comprehensive hospital waste protocols and regulatory standards.
- **Integrate with Embedded Hardware for On-Site Deployment:** Deploy the model on embedded systems such as Raspberry Pi or NVIDIA Jetson Nano to create compact, portable smart bins. This would enable real-time, edge-based waste sorting directly at the point of disposal without relying on external computing infrastructure, making the system more scalable and accessible.
- **Develop a Continuous Learning Framework:** Incorporate feedback-driven retraining using new waste image samples collected from real-world deployments. This will allow the model to adapt over time to variations in waste appearance and operational conditions, thereby maintaining high accuracy and robustness in dynamic hospital environments.

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