**Developing an Advanced Computer Vision-Based Robotic Sorting System for Smart Logistics Optimization**

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**Abstract:** The technology enhances logistics with improved efficiency and accuracy. It combines computer vision and intelligent optimization methods to tackle the issues of speed, precision, and adaptability in sorting, thus offering a pathway toward more advanced smart logistics systems. Develop a computer vision-based robotic sorting system with an enriched Black Widow Optimization-tuned Convolutional Block Attention Module for classifying items with high accuracy and achieving better sorting efficiency and scalability in modern logistics environments. Dataset: Package images from logistics facilities vary in size, shape, lighting, and labels. Resizing images standardizes the dimensions to ensure consistent inputs to the model. Normalization scales pixel intensity values to improve the stability of the model and hasten convergence. HOG captures essential edge and texture features and thereby facilitating the characterization of the package. EBWO is utilized in fine-tuning CBAM to prioritize the feature in the image data so that the robotic sorting can have a precise and efficient item detection. Using Python to implement the proposed system, the results presented an accuracy of 96.21% and an F1 score of 97.38% over traditional methods; it shows efficiency and effectiveness with high precision in achieving real-world sorting scenarios.

**Keywords**: Computer Vision; Robotic Sorting System; Smart Logistics Optimization; Black Widow Optimization tuned Convolutional Block Attention Module (EBWO-CBAM)

## Introduction

Logistics was the fuel behind commodity transportation among different industries, and it's the core of global supply chains [1]. The traditional sorting methods in warehouses and distribution centers were becoming less practical as demand for faster delivery increased [2]. High labor costs, errors, delays, and inefficiencies all hinder the optimization of logistics activities when using manual sorting. As the solutions to these challenges, automation and high-end technologies that can increase the accuracy and speed of the sorting systems with scalability have also become popular remedies [3]. Computer vision was a technology utilizing complex algorithms as well as cameras to enable the robots to examine and read their environment. Once implemented into systems, computer vision enables robotic system to automatically sort objects through real-time item categorization and identification. Together, robotics and computer vision might transform the entire logistics industry due to reduced human error, operational efficiency, and lower direct labor costs [4]. That was made possible through smart logistics optimization by making use of the newest cutting-edge technology, like machine learning (ML), artificial intelligence (AI), and robots, in logistics. To optimize and fortify the supply chain, such systems must be able to analyze all the different motions of the goods, enhance the inventory management process, and offer real-time insights into operations [5]. With the continuously moving market, it became inevitable to pressurize logistics for offering quicker, accurate, and competitive solutions. It was quite difficult for existing commodity sorting and dealing systems to eliminate human dependency with current conventional equipment, as errors due to humans or low efficiency might have to incur to decrease processing speed [6]. The increasing complexity of global supply chains was making it more challenging, requiring faster turnaround times and the ability to handle a greater variety of items in different sizes, shapes, and packaging [7]. The setup costs for that system were high; it relied on good camera equipment, it was sensitive to environmental elements, such as clutter and illumination, and it could not adapt to different types of items.

To develop a computer vision-based robotic sorting system with an enhanced Black Widow Optimization-tuned Convolutional Block Attention Module toward the achievement of high efficiency, accuracy, and scalability in logistics.

**Related work**

To examine robotic control based on computer vision about environmental protection, healthcare, and industrial automation [8]. Among the methods were reinforcement learning, feature extraction, and image recognition. The findings show advancements in waste management, navigation, and object identification. Adaptability and computing complexity were disadvantages. The accomplishment of performance improvement was validated by the statistical analysis. For intelligent sorting applications, the issue statement discusses scalability constraints and real-time processing accuracy. An Openart small camera, Mecanum wheels, and an STM32F103RCT6 microcontroller were part of a mobile sorting system that was precisely controlled via kinematic inverse solutions and cascaded Proportional-Integral-Derivative (PID) [9]. With MobileNet V2, it classifies images with 97% accuracy. Despite improvement in efficiency use still limited by environmental and technological factor. It focuses on how automation may optimize logistics and save labor expenses. Rapid growth in e-commerce necessitates clever logistical solutions. Traditional handling lacks flexibility and relies on preprogrammed duties [10]. To describe a machine vision-based robotic arm control method for versatile item handling. Autonomous navigation, path planning, and image recognition all contribute to increased efficiency. Accuracy was validated by experimental outcomes. The research's ongoing limitation was environmental fluctuation. Precision and flexibility were challenges in intelligent logistics automation. Examined the methodology, statistical test-based discoveries, limitations, and numerical results of computer vision in robots [11]. The improvements in perception, navigation, and task execution with ML and vision sensors were highlighted. The issue statement was created by determining the gaps in the literature and outlining the goal, extent, and importance of creating an intelligent robotics control system [12]. To identify flaws in wheat, oats, and peas, a convolutional neural network (CNN) was employed in the increase of agricultural computer vision employing optical sorting robots [13]. Region-based Convolutional Neural Network (R-CNN) was assessed against Visual Search and Sorting Learning (VISSL) using Open-Source Computer Vision Library (OpenCV), achieving 87% accuracy. Dependency on the dataset and incorrect categorization were examples of potential drawbacks. In agricultural automation sorting processes, that highlights the need for the creation of strong and flexible algorithms. An interactive graphical user interface (GUI) program utilizing Hue, Saturation, and Value (HSV) color identification, shape recognition, and size determination algorithms was developed [14] to construct a robotic vision system for item sorting based on size, shape, and color. The robotic arm's movement was dictated by inverse kinematics, while the centroid detection technique determined the locations of objects. The system's shortcomings include its reliance on pre-set settings and lighting conditions. As a result, it draws attention to the difficulties in automating natural robotic processes.

## Methodology

It focuses on improving robotic sorting performance in smart logistics by utilizing a collection of package images from logistic facilities. After the dataset has been preprocessed to make it uniform in size and normalization, its features are retrieved using the HOG approach, which essentially extracts the images' salient spots. The EBWO-CBAM model is applied to prioritize features for optimized sorting. The outcome demonstrates assessing performance using accuracy, F1 score, error rate, operational efficiency, sorting speed, computational efficiency, and processing latency metrics over multiple epochs. The complete process flow for a robotic sorting system for smart logistics optimization is displayed in Figure 1.

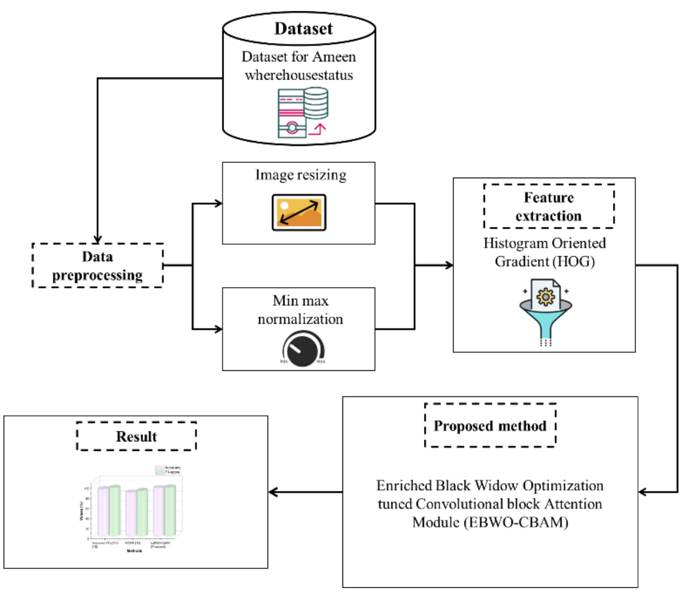



*Figure 1. The complete process flow for a robotic sorting system*

### *Data set*

The warehouse delivery box detection dataset was collected from Kaggle. This dataset is used for detecting objects that include different kinds of delivery boxes in warehouse or storage settings. It comprises a collection of images captured in real-world warehouse environments, under various conditions such as different sizes, orientations, lighting scenarios and sealing. Bounding boxes were expanded systematically around each image to identify delivery boxes accurately, making the dataset appropriate for object detection. It helps support the development of automated systems in logistics and warehousing to enhance tasks like inventory management, package sorting, and autonomous navigation.

Source: https://www.kaggle.com/datasets/zoya77/warehouse-delivery-box-detection-dataset

***Data Preprocessing Steps***

Resizing the image ensures uniform input dimensions throughout the dataset and Min-Max normalization scales the pixel values to a fixed range, enhancing the stability of the models and speeding up convergence for efficient robotic sorting in logistics.

***Image Resizing for Robotic Sorting Systems with Consistent Input Dimensions***

In computer vision-based robotic sorting system design, shrinking images will be an important pre-processing step. The standardizes input image dimensions to enable the model to process it uniformly and appropriately. The scaling of fixed-size images will facilitate easier handling of fluctuations in the scale of objects while maintaining the consistency of feature extraction. It is an optimization that enhances the efficiency of ML algorithms and decreases the computational load on high-precision sorting. Resizing allows the system to run more smoothly in dynamic contexts that are allowed by resizing, which means it is able to correctly identify and detect the objects, regardless of the original size or resolution.

***Optimizing Model Stability in Robotic Sorting via Min-Max Normalization for preprocessing***

Min-max normalization is the process used to normalize images in preparing a computer vision-based robotic sorting system. This pre-processing ensures the balancing of image data within the range of 0 and 1. Using min-max normalization, equitable distribution of data will be ensured. It further improves the accuracy in sorting objects based on size, shape, and lighting conditions. The pixel intensity values from the original data will be linearly converted within the defined range through min-max normalization. Equation (1) can be used to alter the property $B'$s value from $[min_B, max_B]$ to $[new_{min_B}, new_{max_B}]$

$$\frac{u-min_B}{max_B-min_B}\left(new_{min_B}, new_{max_B}\right) + new_{min_B} \tag{1}$$

It ensures that all image information is scaled to a specific range using min-max normalization, thereby increasing the efficiency and accuracy of robotic sorting enabling faster, more precise operations in dynamic logistics environments.

***Feature Extraction Using HOG***

The development of a robotic sorting system using computer vision to create a sorting system based on HOG as the feature extractor. HOG is a type of visual identifier that focuses on how something is composed or made to appear in an image. The histogram of oriented gradients provides unique structures with illumination differences and background noise, which makes it a good descriptor. HOG calculates the gradient directions' incidence in the region of interest. This method utilizes the local gradient of grey levels to determine what kind of structure is embedded in the ROI.

A gradient is known as the direction of gray value differences. Since the value of gradients is so high at boundaries, it has been utilized in obtaining the desired information related to the ROI of interest. In this HOG descriptor, instead it is subdividing the whole ROI into parts or small divisions that are termed cells, where the descriptor would obtain the gradient histogram of every cell. This represents a crucial stage in the design of a robotic sorting system based on visual recognition for the accurate detection and sorting of objects in dynamic logistical environments.

To apply the HOG descriptor, the ROI must be divided into cells, and each cell's gradient in the $w$ and $z$ directions must be obtained. The definition of the gradient is the following equation (2):

$$H_W = J * N_W, \quad H_Z = J * N_Z \tag{2}$$

Where ROI is represented by $J$, $N_W$ mask is in the $w$- and $N_Z$ mask is in the $z$-directions. The ROI's ultimate gradient value is the following equation (3).

$$|H| = \sqrt{H_W^2 + H_Z^2} \tag{3}$$

A single description of the gradient orientation is the following equation (4):

$$\theta = arc\tan\left(\frac{H_Z}{H_W}\right) \tag{4}$$

The gradient in a computer vision-based robotic sorting system is categorized as "unsigned" or "signed," and the graph's units are evenly divided between $0 - \pi \ and \ 0 - 2\pi$. The sum of the gradient values of the gray level with an edge position inside the bin's boundaries determines the bin's magnitude. Blocks, being larger overlapping sections, are utilized to obtain the grayscale value. Blocks are made by collecting cells. Because contrast normalization has been applied, a grayscale rate is calculated for every block and used to normalize cells within blocks. Finally, robotic sorting and exact item classification depend on HOG features created from normalized regions of interest.

***An enriched Black Widow Optimization-tuned Convolutional Block Attention Module (EBWO-CBAM)***

A high-performance sorting robotic system based on computer vision would be demonstrated using the enhanced Black Widow Optimization-tuned Convolutional Block Attention Module, an EBWO-CBAM, for a perfect classification process of items so that scalability would be efficient within the context of modern logistics. The hybrid approach makes use of the superiority of the Black Widow Optimization algorithm while fine-tuning the setting of the innovative CBAM that focuses on key elements of the image. Optimally calibrated parameters ensure that the model will feature excellent feature priority, thus ensuring that the model can identify and categorize a wide range of objects in a logistical setting. The EBWO maximizes the performance of the attention module by instructing it to focus on pertinent elements such as edges, textures, and object contours, which are critical for accurate recognition and sorting. Thus, the hybrid EBWO-CBAM model increases the scalability, resiliency, and efficiency of the system and gives more options for dynamic logistics processes, which require high-speed and high-accuracy sorting.

***Convolutional Block Attention Module (CBAM)***

The CBAM module is used to enhance the suggested computer vision-based robotic sorting system by adding attention mechanisms along the spatial and channel dimensions. Figure 2 illustrates the CBAM design.

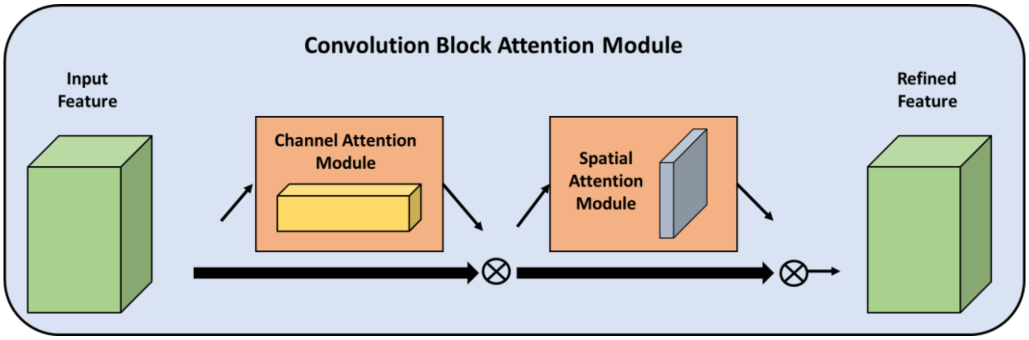



*Figure 2. Illustration of the CBAM Design for Enhanced Feature Prioritization in Robotic Sorting Systems*

The previous 3D CNN uses the input data $W$ to create the feature map$E \in Q^{D\times G\times X}$, where $D$ stands for the number of channels, $G$ for height, and $X$ for width. A channel attention module and a spatial attention module $E$ are used in equation (5) to enhance this feature map to maximize feature extraction for precise item classification and effective robotic sorting in logistics applications.

$$E' = N_d(E) \otimes E, E'' = N_t(E') \otimes E' \quad (5)$$

The feature extraction stage in the development of a robotic sorting system based on computer vision requires careful consideration. In this case, $E'$ would be the outcome of the collective feature plot by the channel attention plot, which $\otimes$ stands for element-wise multiplication. $E''$is the outcome of multiplying the spatial attention plot by $E'$ to get the final output.

***Module for Channel Attention:*** The attention layer isolates the informative channels that primarily convey important features, since each channel in the feature map is a sort of detector. The total average combining and max combining layers are used to get $E'$, where the former helps capture more overall feature information and the latter identifies variability concerning the features in general. $\otimes$ is the operator for element-wise multiplication. When both layers are combined, the system's capacity to identify and classify items effectively in logistical settings is improved. The compressed feature maps $E^d_{avg}$ and $E^d_{max}$, were transmitted to the shared network, which was made up of a single hidden layer and a multi-layer perceptron (MLP), it was configured at an exact density ratio to minimize the parameter and computation to create a robotic sorting system based on computer vision. The channel attention map of $N_d(E) \in Q^{D\times 1\times 1}$ was calculated using the sigmoid function, which was done as follows in equation (6):

$$N_d(E) = \sigma\left(MLP\left(Avgpool(E)\right) + MLP\left(Maxpool(E)\right)\right) = \sigma\left(X_1\left(X_0\left(E^d_{avg}\right)\right) + X_1\left(X_0\left(E^d_{max}\right)\right)\right) \quad (6)$$

$E^d_{avg}$ and $E^d_{max}$ the two combining layers' compressed feature maps are represented, while the sigmoid function is shown by $\sigma$. The MLP's weights are $X_0 \in Q^{D/q\times D}$ and $X_1 \in Q^{D\times D/q}$ , respectively.

***Module for Spatial Attention***: To develop a computer vision-based robotic sorting system which illustrates how crucial the spatial attention module for highlighting feature map regions that are producing high values. Channel attention is further enabled by applying key information region emphasis along with important information regions required for accurate item classification and sorting. This allows for the extraction of two 2D feature maps $E^t_{avg}$ and$E^t_{max}$, along with the channel measurement by relating the total average combining layer and the total max combining layer.

The two feature maps in two dimensions were concatenated to create the active feature map for convolution. After completing the convolution operation in equation (7), the $\sigma$ function computed the spatial attention map as follows by $N_t(E) \in Q^{1\times g\times x}$,

$$N_t(E) = \sigma(e^{7\times7}([AvgPool(E); MaxPool(E)]))) = \sigma\left(e^{7\times7}\left(\left[E^t_{avg}; E^t_{max}\right]\right)\right) \quad (7)$$

Where $E^t_{avg}$ and $E^t_{max}$ sigmoid functions are represented by $\sigma$, while the feature maps compressed in the channel dimension are denoted by $t$ max. It developed to incorporate the attention mechanism of CBAM so that the channel module and spatial module can be cooperative to learn key information both in the station and 3-D dimensions and redistribute the weight of structures adaptively to enhance the precision and efficiency of sorting.

***Enriched Black Widow Optimization (EBWO)***

The development of the search process is significantly influenced by the exploration search method. Using the system's previous sorting experience, the mutation component of the robotic sorting system is altered to investigate the promised area of the system's operating environment. The performance of the exploration process and, consequently, the sorting efficiency of the robotic sorting system are improved by including the new exploration approach in the mutation operator of the system. The fundamental steps of the suggested system will be thoroughly described in the lines that follow.

***Initializing a dynamic pool (DP):*** The suggested method starts by setting up a DP of size $C \times C$, where $C$ is the system dimension. A particular item or sorting parameter in the computer vision-based robotic sorting system is represented by each column in the DP.

***Revising the DP:*** When the robotic sorting system was being developed, the values of the decision variables (DVs) assigned using the mutation operator of acceptable solutions were used to update the system's decision parameters (DP). Row by row, the DV values are entered into their respective columns of the DP; if every row in a particular DP's column is updated, the content of the top row will be replaced with the following update value.

***Using a modified approach to mutation:*** With the mutation of a straightforward operation provided by equation (8), the new suggested mutation strategy is selected at random from the two values extracted from the image dataset that is inside the same block structure, producing a new value of mutation:

$$w^{DV} = DP^{DV}_{q_1} + V(0,1) \times \left(DP^{DV}_{q_2} - DP^{DV}_{q_1}\right),\ q_1 \neq q_2, q_1\ and\ q_2 \in [1, C] \quad (8)$$

Either the conventional mutation strategy or the suggested mutation strategy will be applied to the other strategy once the system randomly selects one of the two mutation methods with equal chance. This technique will assist in increasing the accuracy and efficiency of the robotic sorting system for better item classification and object identification.

**Result & Discussion**

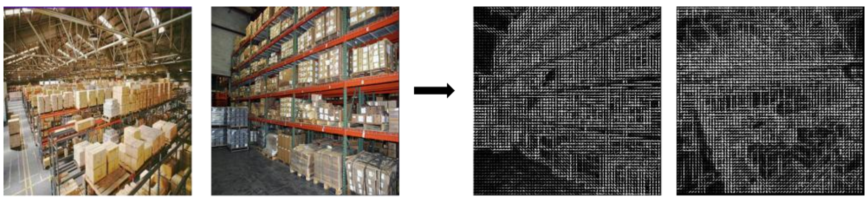
The robotic sorting in smart logistics, the suggested EBWO-CBAM framework's expressive components, and system requirements are shown in Table 1.

*Table 1. System requirements*

| Component | Description |
|---|---|
| Operating System | Windows 10 |
| Python Version | Python 3.11 |
| CPU | Intel i7 |

| | |
|---|---|
| RAM | 32 GB |

To develop an advanced computer vision-based robotic sorting system for intelligent logistics optimization. The image illustrates a warehouse scene with stacks of packed goods on shelves in Figure 3, along with processed versions of the same image utilizing edge detection or point cloud representations. Package recognition, classification, and sorting are made possible for robotic systems by utilizing the techniques, such as edge detection and HOG feature extraction from computer vision. Thus, the entire logistics process becomes more automated, precise, and efficient, warehouse management is improved and human labor is decreased.



**Original Image** **HOG filtered Image**

*Figure 3. HOG Feature Extraction from Warehouse Images for Package Identification and Categorization*

The performance measurements of the suggested EBWO-CBAM model at various epochs in terms of sorting speed, computational efficiency, and processing delay in robotic sorting systems are compiled in Figure 4. As the number of epoch's increases, sorting speed improves. It decreases to 1.2 seconds at 50 epochs from 3.1 seconds at 10 epochs. The range of the computational efficiency is 3.5 to 4.2 seconds. Processing latency noticeably decreases as the number of epoch's increases, standard from 4.2 seconds at 10 epochs to a pitiful 0.5 seconds at 50 epochs. As a consequence, the results indicate throughout training, it gets quicker and more efficient for a real-time sorting position.

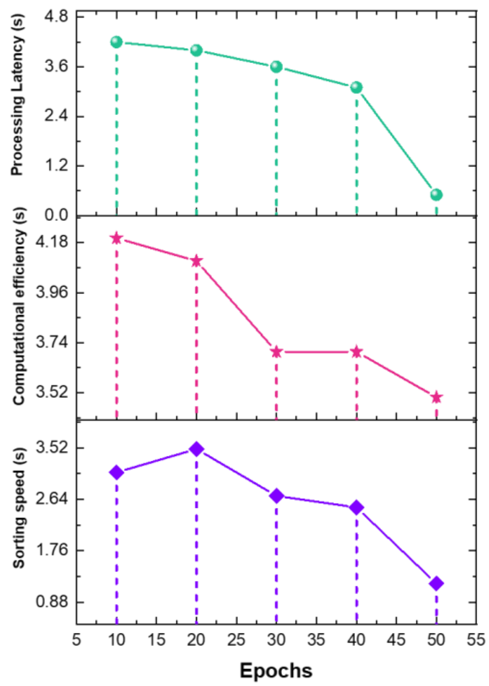



*Figure 4. Evaluation of the EBWO-CBAM Model's Performance*

The EBWO-CBAM robotic sorting system's operating efficiency and error rate with time are displayed in Figure 5. Since the model learns effectively across epochs, increasing the number of epochs lowers the error rate. An error rate of 11.01% at 10 epochs is the starting point. But in the 50th epoch, this sharply drops to 5.01%. At the same time, operational performance efficiency shows a steady rise from 70% at 10 epochs to 90.33% at 50 epochs. This demonstrates how the system is improving in accuracy and efficiency as it gains knowledge, which is in line with the ideal objective of improving sorting performance and scalability in intelligent logistics settings.

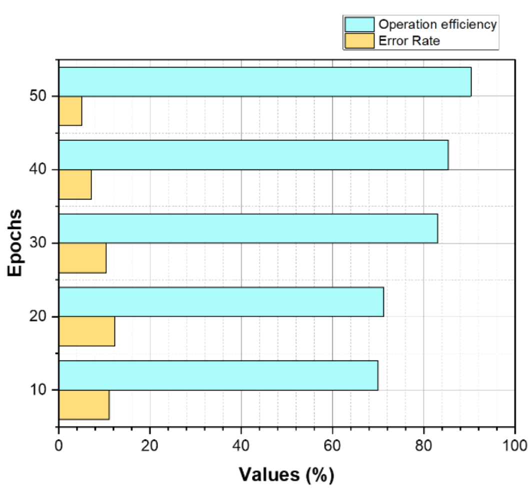



*Figure 5. Assessment of the EBWO-CBAM Robotic Sorting System's Efficiency*

***Accuracy:*** The percentage of correctly sorted objects is determined by the precision metric. The accuracy of the EBWO-CBAM suggested system is 96.21%, while the improved YOLOv3 is 94.05% and that of the RCNN is 87.21%, as shown in Table 2 and Figure 6. The high level of precision shows how well the system performs in correctly categorizing and sorting things in accordance with the goal of improving sorting accuracy in smart logistics.

***F1 score:*** The F1 score is a metric that evaluates how well the model classifies things by combining precision and recall. In this case, the EBWO-CBAM system outperformed the improved YOLOV3 (95.77%) and RCNN (90.5%) with an F1 score of 97.38% as shown in Table 2 and Figure 6. This suggests that it can better balance recollection and classification accuracy for robotic sorting tasks.

*Table 2. Evaluation of Robotic Sorting System Object Detection Model Performance*

| **Methods** | **Accuracy (%)** | **F1 Score (%)** |
|---|---|---|
| Improved YOLOV3 [15] | 94.05 | 95.77 |
| RCNN [15] | 87.21 | 90.5 |
| EBWO-CBAM [proposed] | 96.21 | 97.38 |

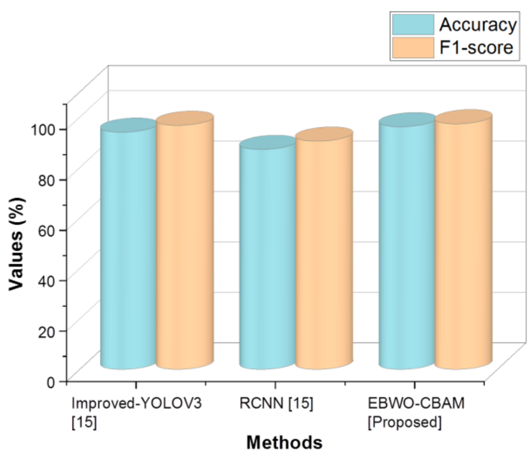



*Figure 6. Comparing the Accuracy and F1 Score of Models for Robotic Sorting Systems*

***Discussion***

To enhance robotic sorting systems based on computer vision for intelligent logistics: improving on current models, such as RCNN [15], and improved YOLOV3 [15], which had respective F1 scores of 95.77% and 94.05% accuracy. However, the present models struggle with accuracy and flexibility in the ever-changing logistics landscape. Furthermore, the majority of models are not resilient to variations in image sizes, shapes, and illumination, which has a detrimental effect on operational effectiveness.

The RCNN model is sluggish and ineffective for real-time applications, particularly in large-scale logistics systems, despite having an accuracy of 87.21% and a 90.5% F1 score. By combining sophisticated attention mechanisms and optimization strategies, the proposed EBWO-CBAM framework solves this issue by giving priority to the most important aspects of images to enhance model performance. The EBWO-CBAM model achieves higher accuracy and F1 score, which improves sorting precision and operational efficiency and, ultimately, optimizes the smart logistics system.

## Conclusion

To demonstrate the creation of an advanced robotic system for sorting applications that is based on the convolutional block attention module that has been modified for richer Black Widow Optimization. The system successfully addresses the primary logistical challenges of the modern world by providing high speeds with accuracy and agility in dynamic environments. The system can precisely recognize and categorize the items using sophisticated preprocessing methods, including scaling, normalization, and HOG feature extraction. Better feature prioritizing is a result of EBWO and CBAM integration has improved sorting efficiency and scalability. It is demonstrated that experimental outcomes outperform conventional techniques in terms of accuracy of 96.21% and F1 score of 97.38%. Developing highly efficient scalable applications in an industrial setting, presents tremendous opportunities to improve the scalability of smart logistics systems.

***Limitations & Future Scope:*** Its reliance on ideal illumination conditions and the possibility of large-scale deployment may be constrained by a lack of computer power. Future work will involve improving system robustness for varying environmental conditions, enhancing object detection capabilities, and improving real-time processing efficiency. The integration of advanced ML techniques can be used to optimize sorting accuracy and adaptability.

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