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Enhancing Navigation and Object Recognition for Visually Impaired Individuals: A Gradient Support Vector Boosting-based Crossover Golden Jackal Algorithm Approach

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ABSTRACT

On a global scale, individuals with vision impairments encounter various limitations when it comes to moving around and finding their way independently. Their daily activities are impeded by their limited understanding of their environment while moving about both indoors and outside, where situations are constantly changing. Recent technological breakthroughs have made it possible to create several electronic devices that help visually impaired and disabled people with navigation. These devices encompass navigation systems, obstacle avoidance systems, object localization devices, and orientation assistance systems. They are designed to enhance or substitute conventional aids like guide dogs and white canes. This research work proposes a solution based on the gradient support vector boosting-based crossover golden jackal (GSB-CGJ) algorithm, which integrates various assistive technologies focused on navigation and object recognition, providing intelligent feedback to the user. The developed model focuses on guiding visually impaired individuals, preventing unwanted collisions with obstacles, and generating active feedback. The proposed method consists of three distinct phases. In the input phase, images are acquired from the Image and Video Dataset for Visually Impaired using Intel RealSense Camera. The next stage entails object recognition, which is efficiently carried out using the GSB-CGJ algorithm. The hyperparameters of the support vector machine and adaptive boosting methods are optimized using the golden jackal optimization method, enhancing object recognition ability. At the end, the output phase delivers feedback to the user. The experimental and assessment results validate that the model demonstrates high accuracy in recognizing objects and precision in localizing them. This approach effectively delivers remarkable real-time implementation capability, showcasing better adaptability and reliability while reducing execution time.

KEYWORDS

visual impairment, visual recognition techniques, gradient boosting, support vector machine, golden jackal optimization

INTRODUCTION

According to the World Health Organization (WHO), about 15% of the total world population has several disabilities such as visual impairment, hearing loss, and locomotor issues. WHO also reveals that there will be an increase in this number because of the gradual increase in the chronic health conditions of aged people (de Freitas et al., 2022). To support these types of disabled people, assistive technology (AT) is used (Kbar et al., 2016, 2017). AT provides various services particularly for aged people to compensate for their functional difficulties. Active participation in life, which includes minimizing the necessity of caregivers and reducing the cost of health care, is also supported by AT. The eyeglasses, prostheses, wheeling chairs, and hearing aids are the few examples of the assistive products (Abdi et al., 2021). Hence, life quality is improved by the technology-based smart and intelligent assistant agents. There are several principles that are stated by "The United Nations Principles for Older Persons" to improve the life quality of the aged people. The major objective of these principles is to focus on the importance of developing assistive surroundings that are highly utilized for the improvement of elder people in terms of mental and physical well-being (Thakur and Han, 2021).

People with several disabilities are assisted by AT in different ways that comprise allowing access to data and education, enhancing the ability to communicate, and performing daily tasks. It also helps an individual to evolve and enhance their skills as well as social inclusion (Ramirez, 2023). Based on individual characteristics as well as personal aspirations, the merits of the assistive products are varied from one person to another. The complication in the AT services leads to the implementation process of the AT services being more complex (Baucas et al., 2021). Various studies state that the efficiency of the information and communication technology (ICT)-based AT is established for the larger set of people with cognitive dysfunction that includes autism spectrum disorder, intellectual disability, acquired brain injury, and developmental disability. It is revealed that ICT-based assistive products such as digital voice recorders and personal digital assistants are employed for individuals with impaired cognition (Brandt et al., 2020). The progress of technological advancements makes the AT more cost-effective by the availability of important ATs, and they are also integrated with the social innovation setting (Nierling and Maia, 2020).

Artificial intelligence (AI)-based solutions are gaining popularity in several fields (Abidi et al., 2022a, b). The ATs of the people who are visually impaired are not easily surrendered without minimizing their independence. The functional needs of the individuals are satisfied by the ATs without causing any social embarrassment. The obstacles are detected by the white cane, and it is also referred to as the symbol by which the blindness of the individuals is communicated. Thus, the white canes are not often utilized by the visually impaired individuals, and the attraction of unnecessary attraction as well as the stigmatization is prevented in which the contact is limited with the individuals who are not blind (dos Santos et al., 2022). The AI-driven solution is exhibited by the OrCam devices that are utilized for visually impaired people in which the individuals can read easily. Thus, AT ranges from the Braille display as well as the books to text-to-speech platforms or wheelchairs (Fiorini et al., 2021). Thus, it is revealed that AT is utilized by people in all views of their daily life including fitness, education, and other daily activities (Söderström et al., 2021). In this work, the gradient support vector boosting-based crossover golden jackal (GSB-CGJ) algorithm is proposed for visual recognition using ATs. The main contributions of the paper are as follows:

Novel architecture: A robust architecture with gradient boosting and a support vector machine (SVM) is created for effective visual recognition. It also uses the best visual impairment dataset for easy processing.

Enhanced recognition: The improvement in recognition is provided by the proposed GSB-CGJ architecture. It processes the data provided efficiently and provides accurate recognition.

Optimization with golden jackal algorithm: The crossover-integrated golden jackal optimization (GJO) fine-tunes the overall performance of the architecture by selecting the optimal hyperparameters.

The remaining sections of the paper are organized as follows: the following section presents the literature review conducted on various works related to the topic of ATs for patients with disabilities; a detailed description of the proposed methodology is given in the Methodology section; the next section provides a detailed explanation of the results and discussions, and the paper is finally concluded with the Conclusions section.

LITERATURE REVIEW

Researchers around the world are working with an aim to make the life of people with disabilities better. With the advent of AI, it is becoming easier, and numerous solutions have been developed. For the paralyzed patients' revival in the connected communities, Jacob et al. (2021) developed an exoskeleton mechanism with the integration of Internet of Things (IoT) and AI. There was an increase in the number of paralyzed people across the world due to the increase in nervous disorders, spinal cord defects, injuries, and stroke. One of the most popular revivals for the paralyzed patients was the exoskeletons. Constant control, adaptability, and instant response were the challenges faced by conventional exoskeletons. To solve the aforementioned challenges, an AI-enabled smart and lightweight exoskeleton system (AI-SES) mechanism was proposed in this article. This mechanism used the data collected by multiple sensors. From the evaluation results, it was found that the proposed mechanism eliminated the challenges faced by the traditional mechanisms and performed well in the navigation functioning. Only a limited number of technologies were explored in this work.

For the revival of neurologically ill individuals, Casey et al. (2021) established a robotic arm functioning with brain–computer interface (BCI). People with neurological disorders were highly dependent on others for their daily activities. Hence, an assistive robotic arm with BCI was a preferred choice. In this work, the arm was controlled with the readings obtained from electromyogram (EMG) and electroencephalogram (EEG). From the simulations done, it was observed that EMG exhibited superior performance and this arm was applied to healthcare use. Various performance enhancements to EEG were not explored in this work.

Based on eye tracking, Paing et al. (2022) developed an assistive mechanism for disabled patients. The assistive mechanisms were used on a large scale for the betterment of disabled individuals. An eye-tracking-based assistive mechanism was proposed in this article to help disabled patients in daily activities. This mechanism was divided into two sections: mobile and stationary assistive mechanisms. The disabled patients were capable of controlling the wheelchairs and home appliances, and sending messages to the caretakers, utilizing their eye movement. From the experiments conducted, it was found that the proposed mechanism showed better performance in assisting disabled patients. The high cost of the mechanism was the limitation of this work.

To incorporate multimodal interfaces, IoT devices, and robotic systems in the medical sector, Brunete et al. (2021) established an intelligent assistive framework. In this work, a multimodal and intuitive interaction mechanism that assists individuals with disabilities was presented. Various home appliances and supportive robots were controlled using this smart assistive framework. For controlling the interactive mechanism, a tablet device was provided in the framework. From the evaluations done, it was found that the usage of mobile phones and eye-based control was preferred among the users.

Based on designing intelligent assistive devices, Wang et al. (2022) illustrated that smart wearable sensor devices help in promoting iteration and digitization of healthcare components used in better manufacturing systems used in rehabilitation assistive devices (RADs). The primary objective of this method was to analyze and improve the item life cycle of the executives and activity system. Research on personalized product-service systems (PSS) for RADs for special populations was scarce, limiting their development. To provide better healthcare services, this study provides a basic overview of IoT-based RAD and PSS-based methods. A few benefits include better efficiency, data availability, and optimization. Some of the drawbacks include complexity issues, high costs, and technical challenges.

Bouteraa (2021) developed a support system for blind and visually impaired people (BVIP). The primary objective of this approach was to enhance safety for BVIP using sensor data. The navigation system utilizes wearable obstacle detection systems controlled by installed controller settings, employing robot operating system planning. It provides a blended mixed haptic-voice message to train visually impaired persons. A few benefits include better scalability, enhanced tracking capability, and good detection.

Malcangi (2021) illustrated that rarely affected diseases provide greater attention in healthcare services due to their impact on nations' economies. The primary objective of this method is to offer various treatments for affected individuals, as neuromotor cell impairments in the brain can lead to serious handicaps. Recent AI advances facilitate early neurodegenerative disease prediction using cutting-edge computational technologies, including advanced artificial neural networks with rapid training and online learning facilities. A few downsides include affecting the overall acceptance of privacy and raising data security issues.

Ciubotaru et al. (2023) developed a preventive method for detecting various health-related effects in the field of research and development. The major goal of this approach was to enhance IoT-based systems in finding frailty. This study helped frame the overall methodology for analyzing various data protocols, advocating for an interdisciplinary approach to interpreting wearable sensor data. It emphasizes visual portrayals and AI models for exhaustive examination. Some of the benefits include better classification, assessability, and good computational analysis. However, there are drawbacks that include affecting system performance, privacy, and security concerns.

Said et al. (2023) presented an obstacle detection system for visually impaired people using deep learning technique specifically modified neural architecture search. The results revealed that the proposed model offered a 2.6% increase in average precision with acceptable computation complexity. Al-Zahrani and Al-Baity also presented a deep learning-based method for object detection. The major contribution from their side is that they proposed a system with Arabic annotation instead of English. The model was based on the Mask region-based convolutional neural network algorithm. The results reported 83.9% accuracy for the model. Tarik et al. (2023) proposed a low cost device for object detection for visually impaired called I-CANe. It provides real-time voice feedback also. Islam et al. (2023) proposed an objection detection system based on TensorFlow object detection application programming interface and SSDLite MobileNetV2. Moreover, gradient particle swarm optimization technique was used in this work to optimize the final layers. The results reported a detection accuracy of 88.89%, a precision of 0.892, and a recall of 0.89.

Research gaps

The usage of AI and sensors in visual recognition for AT among individuals with disabilities yields more benefits compared to other techniques. However, existing works have various limitations such as high implementation costs, insufficient exploration of advanced technologies, lack of comprehensive datasets, and increased execution time. Nature-inspired algorithms have proven to be efficient in several fields (Abidi et al., 2020a, b). To overcome these limitations, this paper proposes the nature-inspired algorithm GSB-CGJ. Based on the literature, the following research gaps are highlighted:

Execution time: Execution time is a crucial parameter for ensuring optimal performance in any mechanism. The GSB-CGJ framework employs proper optimization techniques to fine-tune the performance of the architecture and reduce the execution time.

Recognition accuracy: The accuracy is the main parameter that defines the effectiveness of any framework. The existing works show reduced accuracy due to insufficient datasets. The GSB-CGJ presents a clean dataset and provides better accuracy.

Cost of implementation: The high cost of implementation is the parameter that affects the easy availability of any architecture. GSB-CGJ has a simple architecture and reduced execution time, which make the proposed technique cost-effective.

METHODOLOGY

The workflow of the proposed methodology is shown in Figure 1. Various phases in the process of visual recognition utilizing ATs are presented as follows:

Phase I: the input phase

Visually impaired individuals determine the class of an object based on parameters such as its shape and size, which they identify using their sense of touch. To acquire feedback on the object's content, sound is used. The dataset provided as input is the Image and Video Dataset for Visually Impaired using Intel RealSense Camera.

Phase II: the visual recognition phase using assistive technologies

This phase involves identifying specific visual features from the object by analyzing images from the video stream and

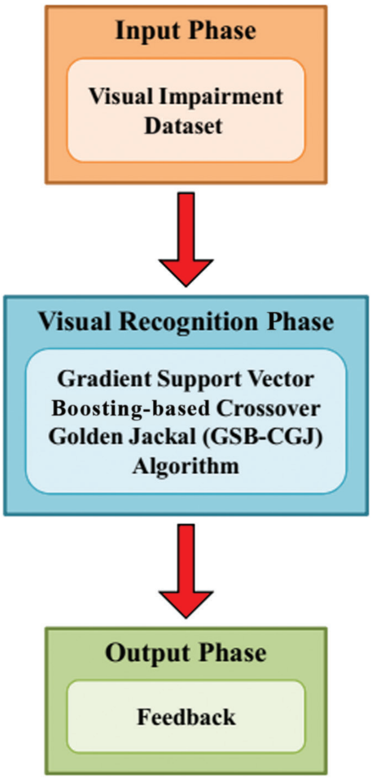

Figure 1: Workflow of the proposed methodology.

the information provided by visually impaired individuals. To execute this task, various image descriptors are analyzed, among which the bag-of-features method demonstrates higher performance in recognition.

Gradient boosting

To solve regression-based tasks, the boosting algorithm plays a major role. $T = \{f_r, b_r\}$ indicating the training dataset is boosted by gradient approach (Douiba et al., 2023). The instances f are plotted based on their predicted values $\widehat{W}(f)$ of the loss function, with $W(f)$ representing their respective output values. The weighted sum of functions present in the gradient boosting is shown based on the following:

$$W_n(f) = W_{n-1}(f) + \sigma_n s_n(f), \tag{1}$$

where the nth function $s_n(f)$'s weight is denoted as σ_n by developing various iterative processes that help in constructing the approximation. The following equation illustrates the constant approximation:

$$W_0(f) = \arg\min_{\delta} \sum_{r=1}^{M} O(b_r, \delta). \tag{2}$$

The predicate decreed in the subsequent approach is shown below:

$$(\sigma_n, s_n(f)) = \arg\min_{\sigma, s} \sum_{r=1}^{M} O(b_r, W_{n-1}, (f_r) + \delta s(f_r)). \tag{3}$$

Whereas $T\{f_r, W(f)\}_{r=1}^{M}$ helps in training every model, the subsequent equation illustrates the computation of pseudo-residuals i_{nr}:

$$i_{nr} = \left[\frac{\partial O(b_r, W(f))}{\partial W(f)}\right]_{W(f) = W_{n-1}(f)}. \tag{4}$$

The line search optimization issues are solved by further evaluating σ_n.

Support vector machine

An SVM algorithm is applied, which employs both regression and utilization effort. It treats every point as the points present in multi-dimensional space, not entirely determined by the features of the data (Wang et al., 2023). Classification is available by detecting the distinct hyperplanes by separating various groups of scattering data points. The following equation indicates the SVM process:

$$\frac{1}{2} w^U w + T \sum_{j=1}^{Q} \xi_j \tag{5}$$

Based on the requirements,

$$z_j (w^U \varphi(y_j) + a) \geq 1 - \xi_j \quad \text{and} \quad \xi_j \geq 0, j = 1, \ldots Q, \tag{6}$$

where T signifies the constant capacity by utilizing vector coefficients denoted as w, managing non-separable data indicated as ξ. Here, the maximum iterations D present in the index j. The class labels and the independent variables are indicated as z_j and y_j, respectively. To avoid more penalties for errors, increased T values lead to a narrower tolerance.

Golden jackal optimization

The golden jackal algorithm is referred to as the swarm intelligence algorithm that was developed by Chopra and Mohsin Ansari (2022). Usually, the golden jackals hunt with both females and males. The hunting behavior of the golden jackal consists of three stages: searching and moving closer to the prey, encircling and irritating the prey, and pouncing toward the prey. In this section, GJO is described and explained step by step. The initial process is to build the solution population, expressed in the equation below:

$$A_j = l_b + t \times (u_b - l_b), \quad j = 1, 2, \ldots, M. \tag{7}$$

From the above equation, the random value is represented by $t \in [0,1]$, whereas l_b and u_b represent parameter limits in the search space. The for each A_j, $A_j = 1,2,\ldots,M$, the fitness value is evaluated to find effective male and female jackal solutions. The matrix of prey is constructed by utilizing the following equation:

$$\text{Prey} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1e} \\ A_{21} & A_{22} & \cdots & A_{2e} \\ \vdots & \vdots & \vdots & \vdots \\ A_{M1} & A_{M2} & \cdots & A_{Me} \end{bmatrix} \tag{8}$$

Exploration stage

The process of hunting is referred to as the model of exploration, and it is based on the female jackal (A_{GN}) as well as the male jackal (A_N) by updating their position in accordance with (A_N); this process is expressed by the equations given below.

$$A_1(u) = A_N(u) - F \times |A_N(u) - t_k \times \text{prey}(u)| \tag{9}$$

$$A_2(u) = A_{GN}(u) - F \times |A_{GN}(u) - t_k \times \text{prey}(u)| \tag{10}$$

From the above equations, A_N and A_{GN} are updated to A_1 and A_2, respectively, with respect to the uth iteration. The prey's energy is represented by F and updated using the equation below:

$$F = F_0 \times F_1, \tag{11}$$

where F_0 and F_1 denote the initial and decreasing energy values from the above equation, respectively. Thus, the values of F_0 and F_1 are updated by utilizing the following equations:

$$F_0 = 2 \times t - 1 \tag{12}$$

$$F_1 = d_1 \times (1 - (u/U)) \tag{13}$$

From the above equations, the maximum number of generations is represented by U, whereas t_1 represents the random value that is developed based on the Levy distribution by utilizing the equation below.

$$t_1 = 0.05 \times \text{Levy}. \tag{14}$$

The jackal positions are updated by applying the following equation:

$$A(u+1) = \frac{A_1(u) + A_2(u)}{2} \times \text{levy}, \ \text{levy} = \frac{m|w \times \eta|}{|\tau|^{1/\delta}},$$
$$\eta = \left(\frac{\Gamma(1+\delta) \times \sin\left(\frac{\varphi\delta}{2}\right)}{\Gamma\left(\frac{1+\delta}{2}\right) \times \delta \times 2^{\left(\frac{\delta-1}{2}\right)}} \right). \tag{15}$$

From the above equation, the random numbers are represented by w and τ, whereas $m = 0.01$ and $\delta = 1.5$ are referred to as constants.

Exploitation stage

In the exploitation phase, GJO provides feasible solutions within the areas that are explored. The hunting of the male and female jackals is represented by this process in GJO, and it is derived by utilizing the equations below.

$$A_1(u) = A_N(u) - F \times |t_1 \times A_N(u) - \text{prey}(u)| \tag{16}$$

$$A_2(u) = A_{GN}(u) - F \times |t_2 \times A_{GN}(u) - \text{prey}(u)| \tag{17}$$

Crossover strategy

The hybridization of the two parent parameters is acquired by employing the crossover operator, and the offspring is attained. It consists of both the parent solution features. The following equation is the crossover that is employed in the present work:

$$w_k = \begin{cases} y_i^k & if \quad c_i \le C_R \\ z_k^i & \text{otherwise} \end{cases}. \tag{18}$$

From the above equation, the crossover rate is indicated by C_R, whereas the two parent solutions are indicated by z_k^i and y_i^k. The probability of crossover is 0.3 in the present work.

The Proposed GSB-CGJ algorithm

AT facilitates active participation in daily life, reducing the reliance on caregivers and lowering healthcare costs. The effectiveness of assistive products varies depending on individual characteristics and personal goals. In order to improve the overall performance of assisting visually challenged individuals in object identification, AI-based assistive mechanisms are employed.

The hybrid model is applied in which more than two distinct and relevant models are employed and the results are combined to form a single value. This paper proposes the GSB-CGJ algorithm, combined with gradient boosting and SVM, to assist visually challenged people in identifying objects by utilizing the AI-based assistive mechanisms. Utilizing the proposed GSB-CGJ helps visually challenged people identify objects, which is improved from the acquired datasets. Adding the diverse models with few hypotheses with respect to the class labels is not seen in other models. Therefore, assisting visually challenged people in identifying objects is performed with high accuracy. It is noted that selecting effective and optimal hyperparameters of GSB is important in assisting visually challenged people in identifying objects. Thus, CGJ is utilized in this paper to optimize the parameters of the GSB algorithm. Then, the transform operator and step size value are multiplied to balance both the local search and global searches. By applying this method, an effective global solution is acquired. Therefore, the attained global solution has a high optimization interval time and a minimum step size value. On the other hand, the CGJ algorithm is subjected to several convergence problems and is easily trapped by the local optima problems. The crossover strategy is added to overcome these limitations to alter the CGJ optimization. The hyperparameters of the GSB algorithm are tuned using the CGJ algorithm to rectify all these difficulties by selecting the best candidate solution and optimal solution. The CGJ algorithm tunes the hyperparameters of the GSB algorithm to overcome all these limitations by selecting the most effective candidate solution. By utilizing the advantages of the CGJ algorithm, the tuning of hyperparameters is carried out. Figure 2 illustrates the flowchart representation of the proposed GSB-CGJ algorithm.

Phase III: the output phase

Finally, in the output phase, the output obtained by the visual recognition phase is presented as feedback in this phase.

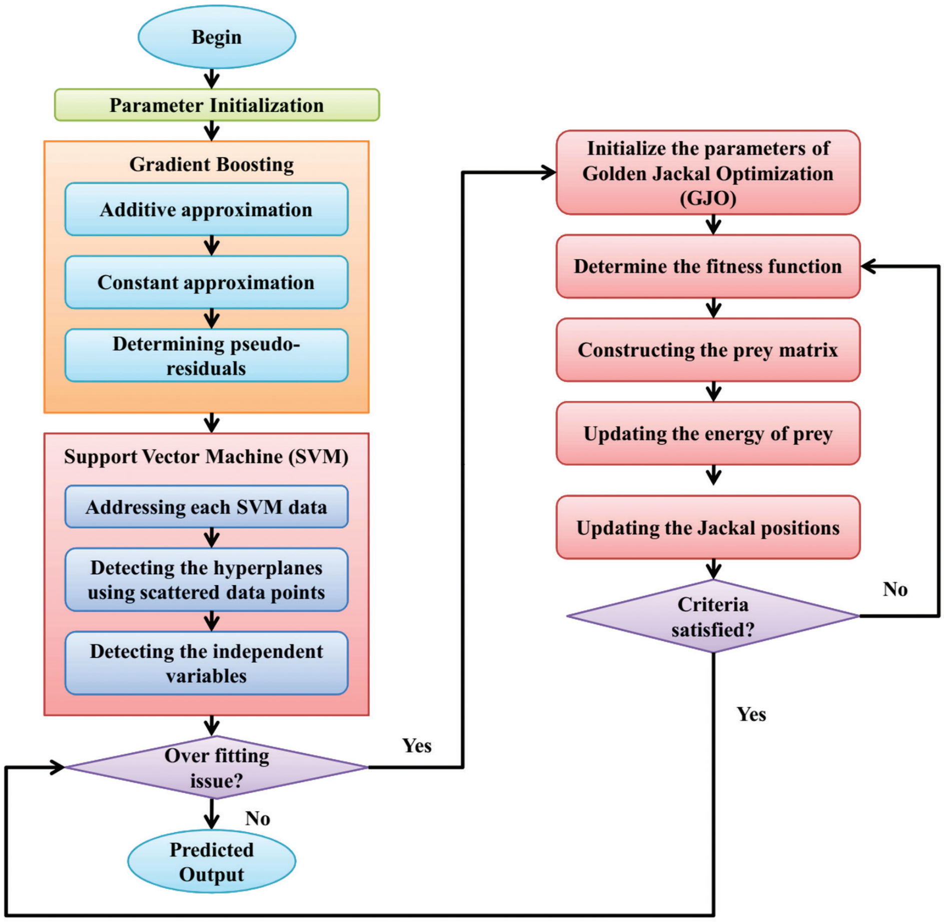

Figure 2: Proposed GSB-CGJ algorithm. Abbreviation: GSB-CGJ, gradient support vector boosting-based crossover golden jackal.

The proposed algorithm, GSB-CGJ, was chosen for several reasons. First, it combines the advantages of SVM and gradient boosting, which are both well-established and widely used machine learning techniques. SVMs are known for their ability to handle high-dimensional data and produce accurate classification results, while gradient boosting is effective at improving the performance of weak learners through ensemble learning. By combining these two methods, GSB-CGJ aims to achieve both high accuracy and robustness in object recognition.

Additionally, the crossover GJO method was chosen for hyperparameter optimization due to its efficiency in finding optimal solutions in complex search spaces. This method is inspired by the hunting behavior of golden jackals, which involves a combination of searching, encircling, and pouncing toward prey. This approach allows for the efficient tuning of hyperparameters in the GSB-CGJ algorithm, further enhancing its performance.

RESULTS AND DISCUSSION

The developed architecture of GSB-CGJ for supporting visual recognition is analyzed in this section for its effectiveness. Here, some evaluation measures are considered for this, and certain existing disability assistance strategies such as evolving fuzzy neural network (EFuNN), AI-IoT-SES, and SVM are used for comparison. The experiments were conducted using the MATLAB platform, and the results are briefly discussed below.

System configuration

The experiments were conducted using a 12th generation Intel Core i7 processor in an HP laptop with 8 GB RAM (random access memory), 512 GB SSD (solid state disk) hard disk memory space, and Windows 11 operating system. The experiments were performed in the MATLAB simulation platform.

Parameter setting

This paper develops a GSB-CGJ algorithm for recognizing objects visually using some ATs. Here, the hyperparameters of the gradient boosting and SVM are optimized using the golden jackal algorithm. Table 1 provides the hyperparameters of these algorithms and their values.

Dataset description

The Image and Video Dataset for Visually Impaired using Intel RealSense Camera constitutes two videos (Mehta

Table 1: Hyperparameters of the GSB-CGJ method.

Methods	Hyperparameter	Values
Gradient boosting	Estimator quantity	100
	Rate of learning	1
	Maximum depth	10
	Maximum number of features	7
	Maximum samples to split	20
	Maximum number of leaf samples	20
SVM	SVM type	One class
	Kernal type	Linear
	Gamma	0.506
	C	312.5
	Iteration	100
	Tolerance error	0.00001
GJO	Size of the population	10
	Iteration	100

Abbreviations: GJO, golden jackal optimization; GSB-CGJ, gradient support vector boosting-based crossover golden jackal; SVM, support vector machine.

and Mehendale, 2023). Both videos are recorded using a 1080p Intel RealSense depth camera: one is captured by blindfolding and the other without blindfolding. The dataset aims to utilize this for machine vision to permit them to operate operations like instance segmentation. To mimic the highly careful gait of a visually impaired person, the captured videos and extracted images with a blindfold were utilized, which supports the generation of the dataset. For instance, the walking activities of a human were recorded by fixing a hat on the head of a blindfolded human. There are 25 videos in the dataset with the frame rate of 30 fps. The image resolution was 1920 × 1080 pixels. For video chunk selection, parameters such as duration (e.g., 10 seconds per chunk) and overlap (e.g., 50% overlap between chunks) were used. The GSB-CGJ algorithm utilized pixels from specific regions of interest within the images, as determined during preprocessing.

Performance measures

The model's performance was evaluated using several common metrics such as accuracy, precision, recall, F1-score, and area under ROC curve (AUC), providing a comprehensive assessment of its ability to recognize objects and its precision in localizing them. The mathematical modeling of these metrics is explained below.

Accuracy

It indicates the values of the ratio of the total correct predictions over the total predictions made by the model. The formula is given below:

$$\mathrm{Ac} = \frac{\alpha_T + \beta_T}{\alpha_T + \beta_t + \alpha_F + \beta_F}. \quad (19)$$

Precision

The positive prediction accuracy is computed as a precision value. The precision is computed using the formula given below:

$$\mathrm{Pr} = \frac{\alpha_T}{\alpha_T + \alpha_F}. \quad (20)$$

Recall

The capacity to capture all related instances is indicated by the term recall. It is specified as below:

$$\mathrm{Sn} = \frac{\alpha_T}{\alpha_T + \beta_F} \quad (21)$$

F1-score

The harmonic mean of precision and recall are referred to as the F1-score. The formula is given below:

$$\mathrm{F1-scr} = 2 \times \frac{\mathrm{pre} \times \mathrm{sen}}{\mathrm{pre} + \mathrm{sen}}. \quad (22)$$

AUC curve

The AUC value is measured by plotting the true-positive rate (TPR) against the false-positive rate (FPR) values.

Performance analysis

The performance of the GSB-CGJ model is assessed to measure the effectiveness of visual recognition, and the results are given in Table 2. Here, the accuracy of the model scores is 94.55%. The precision, recall, and F1-score of the model are 92%, 91.45%, and 94.75%, respectively. Higher performance scores in all the measures indicate higher performance. Based on the figure, it is confirmed that the developed model has admirable performance.

Comparative analysis

The accuracy of the GSB-CGJ model is compared with that of some existing disability assistant methods, shown in Figure 3. The accuracy of the model described here is the effectiveness of the system in detecting objects and recognizing them in indoor and outdoor environments for fully visually impaired patients. This figure shows that the developed

Table 2: The performance of the GSB-CGJ model.

Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
94.55	92.5	91.45	94.75	94

Abbreviations: AUC, area under receiver operating characteristic curve; GSB-CGJ, gradient support vector boosting-based crossover golden jackal.

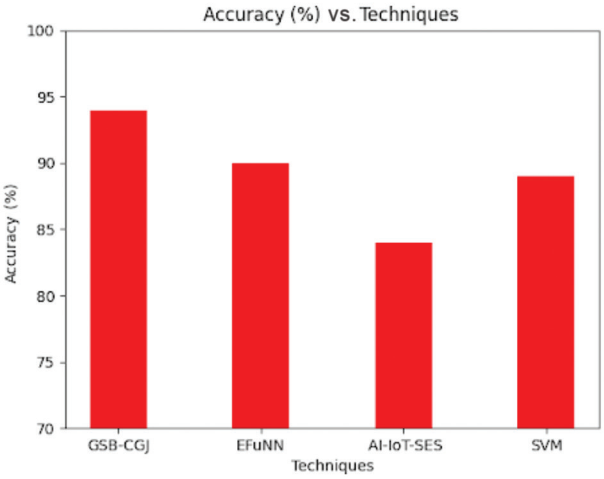

Figure 3: Analysis of visual recognition accuracy of the GSB-CGJ method. Abbreviations: GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

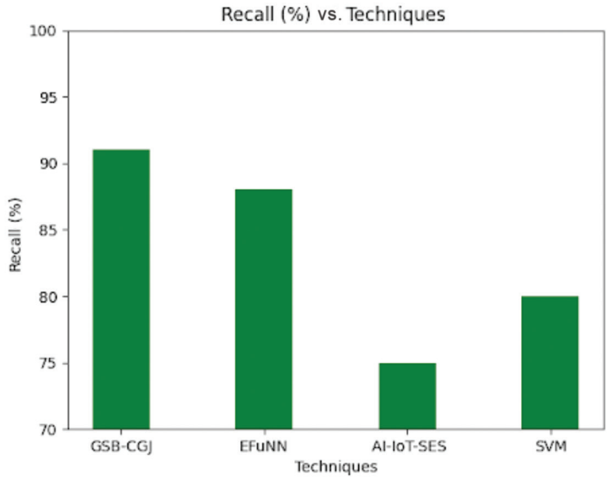

Figure 5: Recall the performance of the developed GSB-CGJ visual recognition strategy. Abbreviations: GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

model has the highest accuracy with 94.55%, which is superior to that of all the existing methods.

Figure 4 analyzes the precision power of the developed GSB-CGJ method by comparing it with certain baselining methods. The precision in this context measures the percentage of the positive prediction generated by the methodology. A higher precision score shows higher visual recognition effectiveness and automatically shows the highest reliability of the model. The observation from the figure implies that the developed model has a higher level of visual recognition precision performance, with a score of 92.5% compared to other underlying methods.

The recall performance produced by the developed GSB-CGJ visual recognition model is compared with that of other methods as shown in Figure 5. Here, recall indicates the whole related instances which are also referred to as the TPR. Greater performance is indicated by a higher recall score. This figure shows that the developed model has the highest recall value with a score of 91.45%. Figure 6 shows the F1-score of the proposed GSB-CGJ methodology. F1-score shows the mean values of recall and precision. Thus the greater values of precision and recall which simultaneously indicates that the higher F1-score performance. From the figure, it is observed that the proposed visual recognition method has a higher level of F1-score performance compared to other existing methods. The area beneath the receiver operating characteristic (ROC) curve is another measure that is utilized to analyze the visual recognition potential by comparing it with other underlying techniques. The range of the AUC score should lie between 0.5 and 1 for

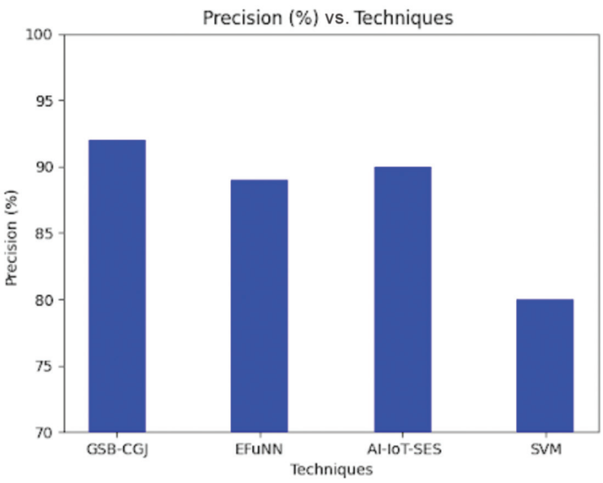

Figure 4: Comparing the precision performance of all disability-assistive methods. Abbreviations: GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

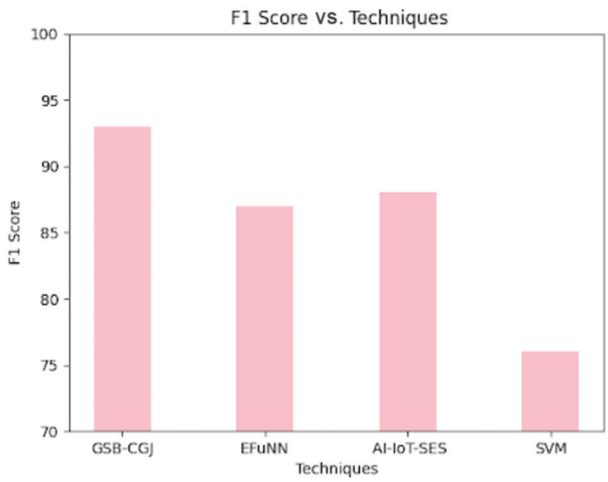

Figure 6: Analysis of the F1-score of the various disability-assistive methodologies. Abbreviations: GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

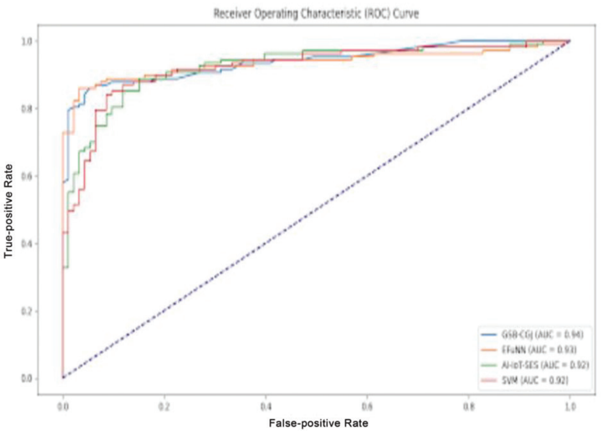

Figure 7: AUC score analysis of the proposed GSB-CGJ methodology. Abbreviations: AUC, area under receiver operating characteristic curve; GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

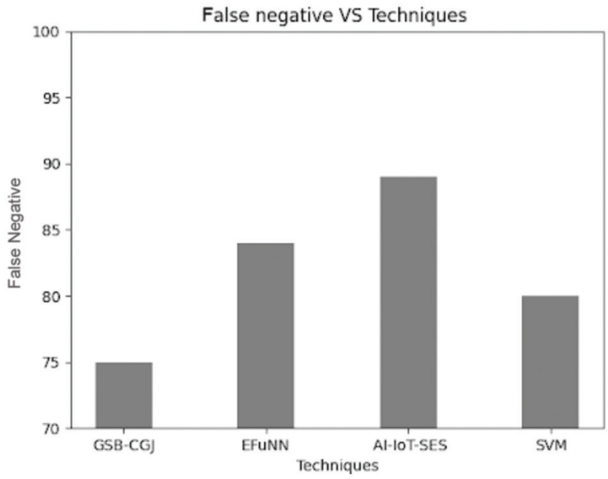

Figure 9: Comparison of the FNR values of all disability-assistive strategies. Abbreviations: FNR, false-negative rate; GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

the productive strategy. This analysis demonstrated that the developed GSB-CGJ model has a superior level of performance with a higher AUC score of 94% (Figure 7).

The errors made by the developed GSB-CGJ methodology are analyzed using two metrics: FPR and false-negative rate (FNR). The FPR is shown in Figure 8 and the FNR is shown in Figure 9. The lesser error values, such as the low FNR and FPR scores compared to all models, posed excellent performance. Figures 8 and 9 show that the developed model has the lowest scores of FPR and FNR, which indicate excellent visually impaired assistive performance.

The time taken by the disability-assistive methods to finish their tasks successfully is referred to as the execution time. The time for execution is influenced by multiple factors, such as the algorithm's complexity, the input's size, etc. The proposed model has excellent visual detection performance and less complexity. This automatically decreases the processing time. The execution times of various methods are shown in Figure 10.

The performance of the GSB-CGJ model is shown in Table 3. Here, some requirements that should be satisfied by the AI-based ATs for visually impaired people are taken. Some existing strategies are also checked to determine whether they satisfy these requirements. The analysis showed that the developed model has an excellent assistive capacity to support visually impaired persons compared to the other existing disability-assistive AI strategies. In this table, H denotes high, M denotes moderate, and L denotes low. Furthermore, Y specifies yes, which is the availability of the corresponding feature, and N means no, indicates the absence of this feature.

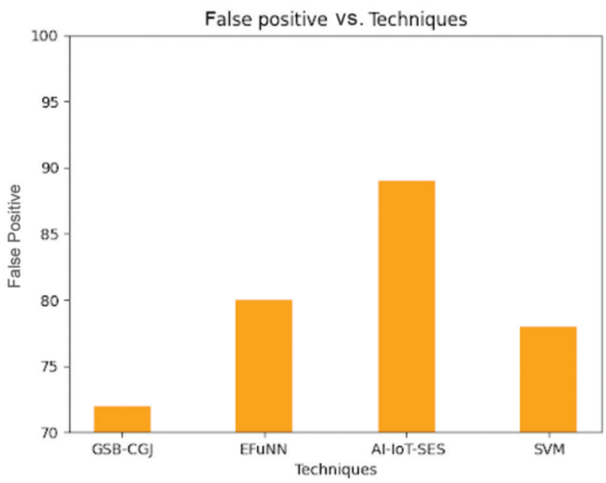

Figure 8: Comparison of the FPR values of disability-assistive techniques. Abbreviations: FPR, false-positive rate; GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

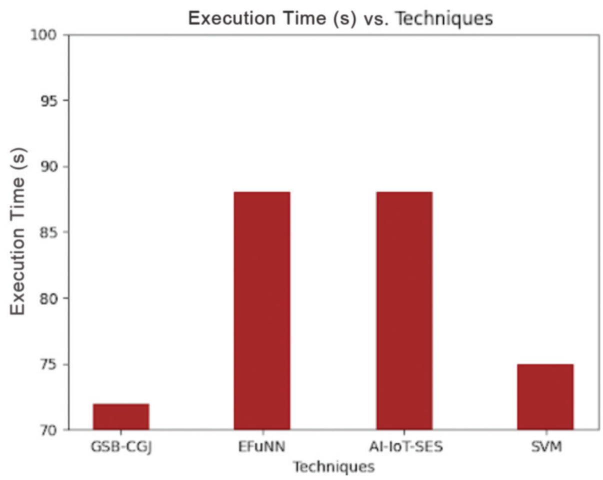

Figure 10: Comparison of the execution time of various disorder-assistive methods. Abbreviations: GSB-CGJ, gradient support vector boosting-based crossover golden jackal; IoT, Internet of Things; SES, smart and lightweight exoskeleton system; SVM, support vector machine.

Table 3: Comparison of various disability-assistive strategies.

Methods	Adaptability	Reliability	Flexibility	Real-time implementation
GSB-CGJ	H	H	Y	Y
EFuNN	M	M	Y	N
AI-IoT-SES	M	M	N	Y
SVM	L	M	N	Y

Abbreviations: AI, artificial intelligence; GSB-CGJ, gradient support vector boosting-based crossover golden jackal; H, high; IoT, Internet of Things; L, low; M, moderate; N, no; SES, smart and lightweight exoskeleton system; SVM, support vector machine; Y, yes.

CONCLUSIONS

The rapidly moving life in the recent decade has caused visually impaired people to face multiple difficulties due to the crowding of the obstacles in the surroundings. Thus, it is necessary for them to depend on external assistance offered by humans, dogs, and multiple advanced electronic support systems to make decisions. A large number of blind individuals seek the development of assistive devices to support and facilitate the normal lives of visually impaired people. Many existing strategies have the disadvantage of detecting obstacles at ground or waist levels, but they do not have the capacity to detect them simultaneously. Therefore, this study develops GSB-CGJ to visually recognize objects with the assistance of various assistive strategies. The developed method gained input images from the Image and Video Dataset for Visually Impaired using an Intel RealSense Camera. Finally, GSB-CGJ recognizes the objects. The ability of the model to be analyzed with some common metrics and three already available assistive AI strategies for disabled persons, such as EFuNN, AI-IoT-SES, and SVM, is compared. The results showed the developed model's higher level of performance with higher visual recognition capability and greater adaptability, trustworthiness, and object localization precision for detecting the obstacles precisely. It lessened the time and cost considerably, which is another advantage.

Once trained, the model can be deployed on a device equipped with a camera, such as a smartphone or wearable device. In real time, the device captures images of the user's surroundings and processes them using the trained model to recognize objects and provide feedback to the user. The feedback may include audio cues, vibrations, or text-to-speech output, depending on the user's preferences. The practical implementation also involves considerations for scalability, computational efficiency, and user interface design. The model should be lightweight enough to run on resource-constrained devices while still maintaining high accuracy. Additionally, the user interface should be intuitive and accessible to visually impaired individuals, allowing them to easily interact with the system and receive meaningful feedback about their environment.

While our proposed approach shows promising results, there are several limitations to consider. First, the performance of the model may vary depending on the quality and consistency of the input data. Variations in lighting conditions, object textures, and background clutter can impact the accuracy of object recognition. Additionally, the model may struggle with detecting objects that are occluded or partially obscured. Furthermore, the computational resources required to train and deploy the model may be prohibitive for some users, particularly those in resource-constrained environments. Finally, the model's performance may degrade when applied to real-world scenarios that differ significantly from the training data. Despite these limitations, our approach represents an important step toward improving navigation and object recognition for visually impaired individuals.

In the future, this model will be extended to include multiple data modalities such as video, audio, etc. Furthermore, the model will be examined with 3D images instead of 2D to evaluate precision further.

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COMPETING INTEREST

The authors declare no conflicts of interest in association with the present study.

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