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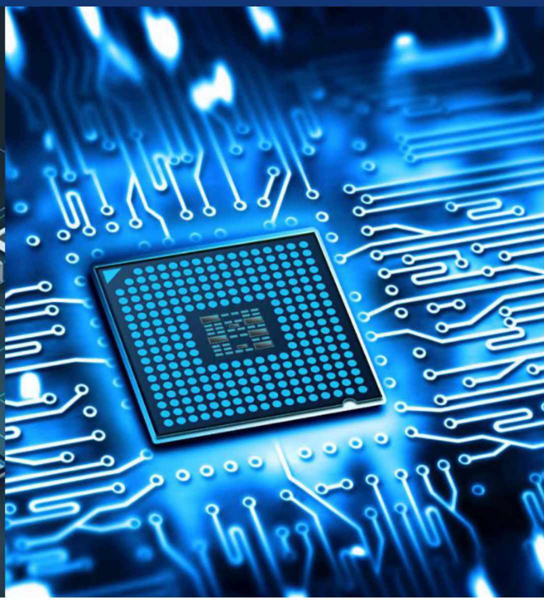


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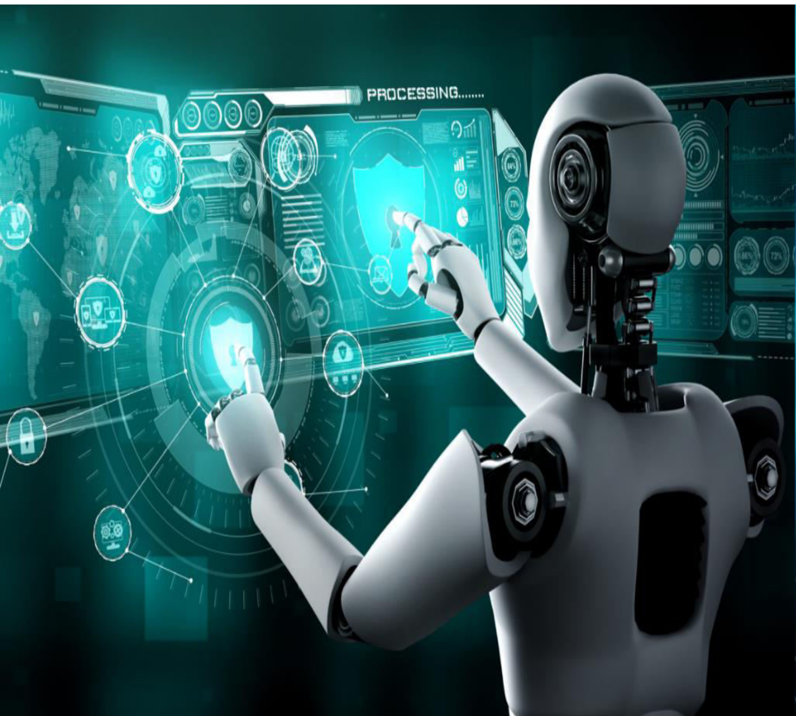

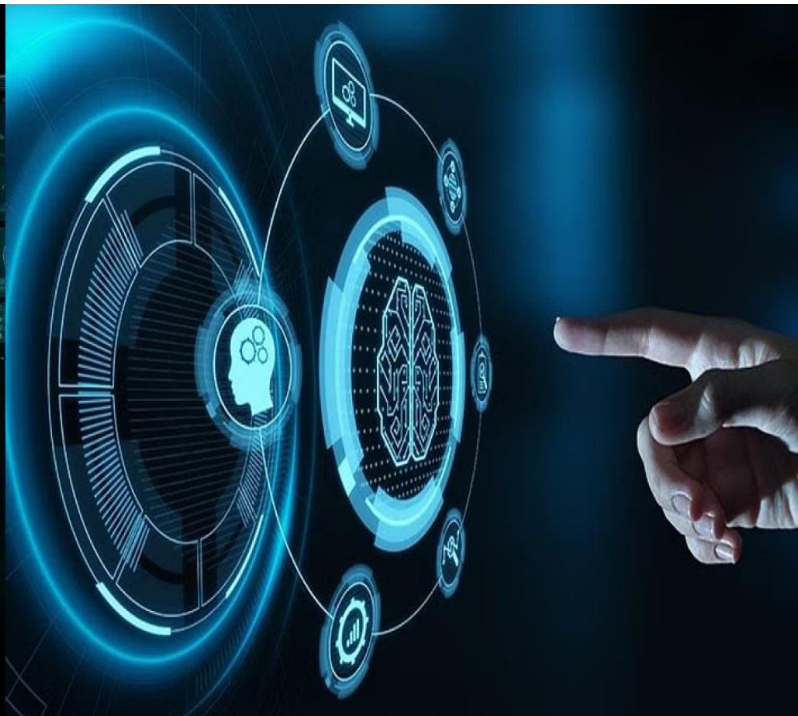

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# Smart Glasses Powered by AI for the Blind and Visually Impaired

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**Abstract:** This paper presents an AI-powered smart glass system designed to assist blind and visually impaired individuals by accurately interpreting their surroundings in real time. The system integrates multiple advanced techniques across the computer vision pipeline to ensure robustness and accuracy. Initially, Anisotropic Diffusion Filtering is employed as a pre-processing step to enhance image quality by reducing noise while preserving important edge details, which is critical for reliable feature extraction. The most pertinent characteristics are then chosen from the visual input using particle swarm optimization, improving computational efficiency and classification accuracy by avoiding redundant or irrelevant information. For classification, a hybrid Convolutional Neural Network and Gated Recurrent Unit model is used, combining the spatial feature extraction capabilities of CNNs with the temporal sequence learning strength of GRUs. This hybrid model effectively interprets dynamic scenes and object patterns, providing real-time feedback to users. The system's performance is evaluated using standard metrics such as accuracy 96.4%, precision 95.8%, recall 96.9%, and F1-score 96.3%, demonstrating high effectiveness in object recognition and obstacle detection. Overall, the proposed framework significantly enhances the navigational capabilities and situational awareness of visually impaired users in complex environments.

**KEYWORDS:** Anisotropic Diffusion Filtering, Particle Swarm Optimization, CNN and GRU

## I. INTRODUCTION

Recent advancements in assistive technologies have significantly improved the independence and quality of life for visually impaired individuals through the integration of artificial intelligence and machine learning. Smart glasses, powered by deep learning algorithms such as YOLOv8, provide real-time object detection and navigation support to aid outdoor mobility, as demonstrated by [1] Similarly, [2] emphasize human-centric design principles combined with machine learning in smart footwear, highlighting the growing trend toward wearable assistive devices. [3] Explore the use of deep learning in smart glass systems that enhance environmental awareness for the blind.
Innovations continue with [4] and [5], who develop AI-enabled smart glasses tailored to visually impaired users, aiming to deliver effective, accessible, and real-time assistance.

### Objectives

- To enhance image quality through Anisotropic Diffusion Filtering by reducing noise while preserving critical edge and structural details necessary for feature extraction.
- To implement Particle Swarm Optimization for selecting the most relevant features from pre-processed images, thereby improving computational efficiency and classification performance.
- To develop a hybrid classification model by combining Convolutional Neural Networks for spatial feature extraction and Gated Recurrent Units for learning temporal dependencies in dynamic scenes.

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## II. RELATED WORK

**Hekal et al. (2024)** The proposed system leverages object detection and scene understanding to enhance user navigation and environmental awareness. Utilizing convolutional neural networks (CNNs), the glasses interpret real-time video input and provide auditory feedback to users. The research highlights the effectiveness of deep learning in improving assistive technologies through increased accuracy and speed. **Badawi et al. (2024)** present a smart bionic vision system designed to assist visually impaired individuals using artificial intelligence. The system integrates object recognition, obstacle detection, and voice-based feedback to enhance user navigation and independence.

**Naayini et al. (2025)** explore the application of AI-powered assistive technologies aimed at supporting individuals with visual impairments. Their study discusses various innovations including smart glasses, voice-assisted systems, and real-time object recognition tools. The integration of deep learning and computer vision enables accurate environmental interpretation and responsive feedback. The authors highlight the role of AI in enhancing autonomy and situational awareness. **Nasser et al. (2024)** propose AI and IoT-enabled mobile applications to enhance mobility for visually impaired individuals. Their system provides auditory cues and adaptive path guidance to support independent movement.
**Souza et al. (2024)** The review covers advancements in smart wearables, ambient intelligence, and AI-driven systems designed to aid navigation and daily activities. **Lavric et al. (2024)** the study explores how VLC enhances data transmission for real-time guidance and situational awareness. AI is highlighted for its role in object detection, path finding, and adaptive feedback systems. The authors stress the potential of combining these technologies for low- latency, high-accuracy solutions.

**Nashtan et al. (2025)** the study categorizes devices based on functionality, such as navigation aids, reading tools, and object recognition systems. It highlights the integration of AI,sensors, and wearable technologies in modern solutions. The authors also discuss affordability, accessibility, and user-friendliness as key factors for adoption. **Arsalwad et al. (2024)** introduce YOLOInsight, The system employs the YOLO algorithm for fast and accurate identification of surrounding objects.

**Varshney et al. (2025**) the study focuses on user experience, comfort, and effectiveness in daily life scenarios. Feedback from participants indicated improvements in navigation, object detection, and confidence during independent movement. The authors emphasize the importance of ergonomic design and intuitive interfaces. **Baig et al. (2024)**. The system enhances the user's perception by providing detailed descriptions of surroundings and objects through natural language feedback. Leveraging advanced deep learning techniques, it delivers accurate and context-aware assistance.

**Badawi et al. (2024)** the system incorporates advanced artificial intelligence algorithms. It provides auditory and haptic feedback to improve navigation and obstacle avoidance. **Busaeed et al. (2022)**. The device combines low-power algorithms with Arduino hardware and a smart mobile app for efficient real-time object detection and navigation support. It emphasizes energy efficiency while maintaining high accuracy in environmental awareness.

**Rao et al. (2021)** The device uses computer vision techniques to detect objects, text, and obstacles, providing auditory feedback. Their approach enables hands-free, continuous environmental awareness and navigation support. **Li et al. (2023)** the system integrates smart sensors and AI algorithms for real-time environment sensing, object detection, and navigation aid. It provides multimodal feedback, including audio and haptic alerts, to enhance user safety and independence.

**Choudhary et al. (2023)** the system uses IoT connectivity for real-time data processing and identification of known individuals. It provides audio feedback to alert users about nearby people, enhancing social interactions and safety.

## III. PROPOSED METHODOLOGY

The suggested approach for the AI-powered smart glass system is intended to give blind andVI people a reliable, effective, and real-time assistive solution. The raw images undergo Anisotropic Diffusion Filtering in the pre-processing stage, which significantly enhances image quality by smoothing noise while retaining critical edges, ensuring the reliability of downstream analysis. Next, the feature extraction and selection phase is performed using Particle Swarm Optimization. PSO intelligently selects the most informative and discriminative features from the filtered images, reducing redundancy and improving the speed and performance of classification.

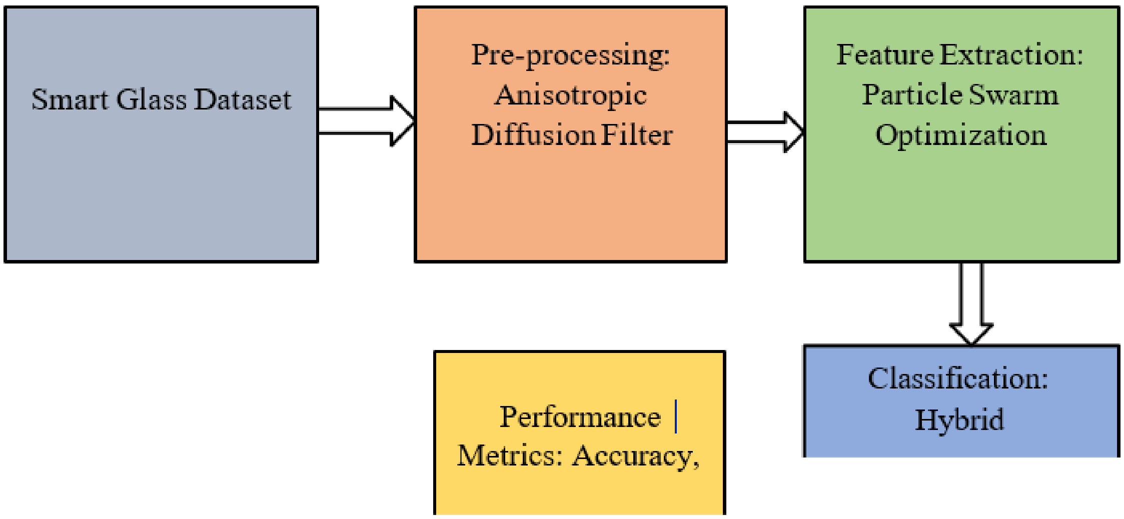


Figure 1 Proposed Methodology Architecture

Figure 1 proposed methodology architecture integrates data acquisition, preprocessing, feature extraction, and classification modules in a streamlined workflow. Initially, raw data is collected and cleaned to enhance quality. Next, relevant features are extracted to capture essential patterns. Finally, these features are fed into a classification model to generate accurate predictions or decisions.

**3.1 Pre-processing: Anisotropic Diffusion Filter**

In AI-powered smart glass systems designed for blind and visually impaired users, preprocessing of visual data is a critical step to ensure accurate and reliable object detection and scene understanding. The anisotropic diffusion filter is employed as an advanced image enhancement technique that effectively reduces noise in the input images while preserving important edges and structural details. Unlike conventional smoothing filters that blur edges and fine features, anisotropic diffusion selectively smooth's homogeneous regions but maintains sharp boundaries by controlling the diffusion process based on local image gradients.

$$\frac{\partial f(i,l,r,t)}{\partial t} = div[q(i,l,r,t)] \quad (1)$$

Where $f(i,l,r,t)$ represents the image intensity at spatial coordinates, $\frac{\partial f(i,l,r,t)}{\partial t}$ is the partial derivate of the image intensity f with respect to time t. this term represents the rate of change of the image during the diffusion process, $div[q(i,l,r,t)]$ is the diffusion coefficient at spatial coordinates $i$, $l$, $r$, and time t.

$$q(i,l,r,t) = \frac{1}{1+[\frac{|\nabla f(i,l,r,t)|^2}{f(i,l,r,t)} - p^2]/(p^2(1+p^2))} \quad (2)$$

Where $q(i,l,r,t)$the diffusion coefficient at is spatial coordinates, $\nabla f(i,l,r,t)$ is the spatial gradient of the image intensity, indicating rapidly the image intensity changes at points, p is the predefined constant parameter that controls the sensitivity of the diffusion process, often related to edge thresholding.

$$q(h) = \frac{1}{1+[h^2(i,l,r,t)-h_0^2(t)]/[h_0^2(t)(1+h_0^2(t))]} \quad (3)$$

$$h_0(t) = \frac{\sqrt{var[z(t)]}}{\overline{z(t)}} \quad (4)$$

Where h represents a function related to the image gradient magnitude local intensity variation, used to adjust the diffusion coefficient adaptively, $h_o(t)$ represents a time-dependent threshold reference value computed from the variance of a signal $z(t)$ and $\sqrt{var[z(t)]}$ represents variance of the signal$z(t)$, measuring its variability over time space, influencing the diffusion strength

**3.2 Feature Extraction: Particle Swarm Optimization (PSO)**

In the context of smart glasses, PSO is employed to enhance the feature extraction process by selecting the most relevant features from sensory data, such as images or sounds, captured by the wearable device. The algorithm evaluates the importance of each feature based on its contribution to the overall performance of the system, such as object recognition or environmental awareness.

$$v_i(t+1) = w * v_i(t) + c_1 rand\,(p^{best\,i} - p_i(t)) + c_2 rand\,(p^{best} - p_i(t)) \quad (5)$$

Where $v_i(t+1)$ is the updated velocity of particle I at time t+1 and $v_i(t)$ is the current velocity of particle i at time t and w is the inertial weight that controls the impact of the previous velocity, $c_1$ and $c_2$ are acceleration coefficients, $p^{best\,i}$ is the personal best position of particle i and $p^{best}$ is the global best position.

$$p_i(t+1) = p_i(t) + v_i(t+1) \quad (6)$$

The updated position of particle I at time t+1 is denoted by $p_i(t+1)$, its current position at time t is denoted by $p_i(t)$, and its updated velocity at time t+1 is denoted by $v_i(t+1)$.

**3.3 Classification: Hybrid Convolutional Neural Network and Gated Recurrent Unit**

Convolutional Neural Network to facilitate object detection and scene comprehension in real time. This technology uses cameras built into the smart glasses to take pictures of the surroundings, which the CNN then analyses to identify and categories text, objects, or impediments.

$$S(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n).\,W(m,n) + b \quad (7)$$

Where $S(i,j)$ coordinates of the output feature map and $X(i+m,j+n)$ is pixels value from the input image, $W(m,n)$ is weight at position (m,n) and M,N is height and width of the filter, bias term added to the convolution result.

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$$S(i,j) = \max_{m=0}^{k-1} \max_{n=0}^{k-1} X(i+m, j+n) \quad (8)$$

Where $S(i,j)$ is output of the pooling operation at position (i,j) and $X(i+m, j+n)$ is region of the input feature map being pooled, k size of the pooled window. Max takes the maximum value from the region, reducing the dimensions and introducing translation invariance

$$y = f\left(\sum_{i=1}^{n} W_i x_i + b\right) \quad (9)$$

Where $y$output of a neuron is after applying the activation function, f is activation function applied to the weighted sum, $W_i$ is weight associated with input $x_i$ input feature value, b is bias term and n number of input features.

The AI-powered system for blind and visually impaired individuals integrates smart glasses with a robust classification mechanism based on Gated Recurrent Units.In this system, the GRU model processes input data such as images or spoken instructions and classifies environmental cues, objects, or obstacles, aiding navigation and situational awareness.

$$K_l = \sigma(W_z . [h_{t-1}, x_t] + b_z) \quad (10)$$

Where $K_l$ is represents the update gate vector at time and $W_z$ is the weight matrix for the update gate. It is learned during trained and helps transform the input and previous hidden state, $[h_{t-1}, x_t]$ represents denotes the concatenation.

$$h'_t = \tanh(W . [r_t * h_{t-1}, x_t] + b) \quad (11)$$

Where $h'_t$ represents candidate hidden state, It is learned during training and transformers the combined input, $r_t$ is the reset gate at time, $h_{t-1}$ is the previous hidden state holds information from the past sequence, $[r_t * h_{t-1}, x_t]$ represents the concatenation of the reset-modified hidden state and the current input.

## IV. RESULT & DISCUSSION

The incorporation of Anisotropic Diffusion Filtering immensely enhanced image sharpness, and the model was able to extract more meaningful features. Besides, Particle Swarm Optimization optimized feature selection had been utilized, diminishing computational burdens and enhancing model convergence. The hybrid CNN-GRU model effectively merged spatial and temporal learning, surpassing usual CNN-only or RNN-only models in coping with dynamic visual environments.

### 4.1 Data Description

The OCOSense eyewear system from Emteq was utilised to gather data. It has three inertial sensors (accelerometer, gyroscope, and magnetometer), a pressure sensor (barometer), and proximity and navigation sensors that record skin movement in three different directions. A constant 50Hz sampling rate is applied to the sensors.

| 1 | Acceleron | Acceleron | Acceleron | Gyroscope | Gyroscope | Gyroscope | Magneton | Magneton | Magneton | Euler/Raw |
|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 9.289974 | -1.51003 | -0.66003 | -0.12493 | 7.499776 | -9.0624 | -31.1875 | 28.75 | 15.875 | 4.042969 |
| 3 | 9.090007 | -1.7 | -0.60998 | 1.50016 | 9.81248 | -14.0001 | -32.6875 | 28.75 | 13.875 | 4.053955 |
| 4 | 9.240003 | -1.80003 | -0.48996 | 0.75008 | 12.31258 | -15.1875 | -32.6875 | 28.75 | 13.875 | 4.075928 |
| 5 | 9.37001 | -1.39002 | -0.27001 | -2.93734 | 14.43738 | -17.3123 | -31.5625 | 27.5625 | 14.6875 | 4.141846 |
| 6 | 9.579971 | -1.23003 | -0.03998 | -6.5623 | 14.31245 | -19.1877 | -31.5625 | 27.5625 | 14.6875 | 4.240723 |
| 7 | 9.650012 | -1.01999 | 0.009994 | -6.75021 | 10.56256 | -20.1252 | -32.375 | 27.5625 | 15.0625 | 4.328613 |
| 8 | 9.859973 | -0.28 | 0.009994 | -4.81229 | 5.499904 | -19.6874 | -32.375 | 27.5625 | 15.0625 | 4.416504 |
| 9 | 9.82999 | 0 | 0.019988 | -1.4377 | 0.999936 | -15.3124 | -32.375 | 27.5625 | 15.0625 | 4.482422 |
| 10 | 9.559982 | -0.23003 | -0.03998 | -0.99994 | -1.56262 | -5.81274 | -33.5 | 26.875 | 14.6875 | 4.515381 |
| 11 | 9.780019 | -0.13001 | -0.14 | -2.3127 | -3.25018 | 6.18752 | -33.5 | 26.875 | 14.6875 | 4.515381 |
| 12 | 9.73996 | -0.00999 | -0.23003 | -1.50016 | -6.06259 | 15.81261 | -34.1875 | 26.1875 | 15.875 | 4.537354 |
| 13 | 9.529999 | -0.50004 | -0.37003 | 0.75008 | -9.75002 | 20.06272 | -34.1875 | 26.1875 | 15.875 | 4.449463 |

Figure 2 Smart glass dataset

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Figure 2 presents a snapshot of the smart glass dataset, consisting of sensor readings from the accelerometer, gyroscope, and magnetometer across three axes. These values help detect motion, orientation, and environmental changes. The dataset also includes Euler angles, providing precise user orientation.

### 4.2 Comparison Results

**Table 1 comparison table results**

| Model | Accuracy | Precision | Recall | FI-Score |
|---|---|---|---|---|
| Support Vector Machine | 85.7% | 84.3% | 83.9% | 84.1% |
| Random Forest | 88.5% | 87.9% | 86.3% | 87.1% |
| Decision Tree | 91.2% | 89.6% | 90.1% | 89.8% |
| Proposed CNN-GRU | 96.4% | 95.8% | 96.9% | 96.3% |

Table 1 shows that the proposed CNN-GRU model outperforms traditional classifiers in all metrics. It achieved the highest accuracy (96.4%), precision (95.8%), recall (96.9%), and F1- score (96.3%). Decision Tree followed with moderate performance (91.2% accuracy), while Random Forest and SVM scored lower. PSO-based feature selection and anisotropic diffusion filtering further enhanced accuracy. This confirms the model's effectiveness for real-time assistance in smart glass systems.

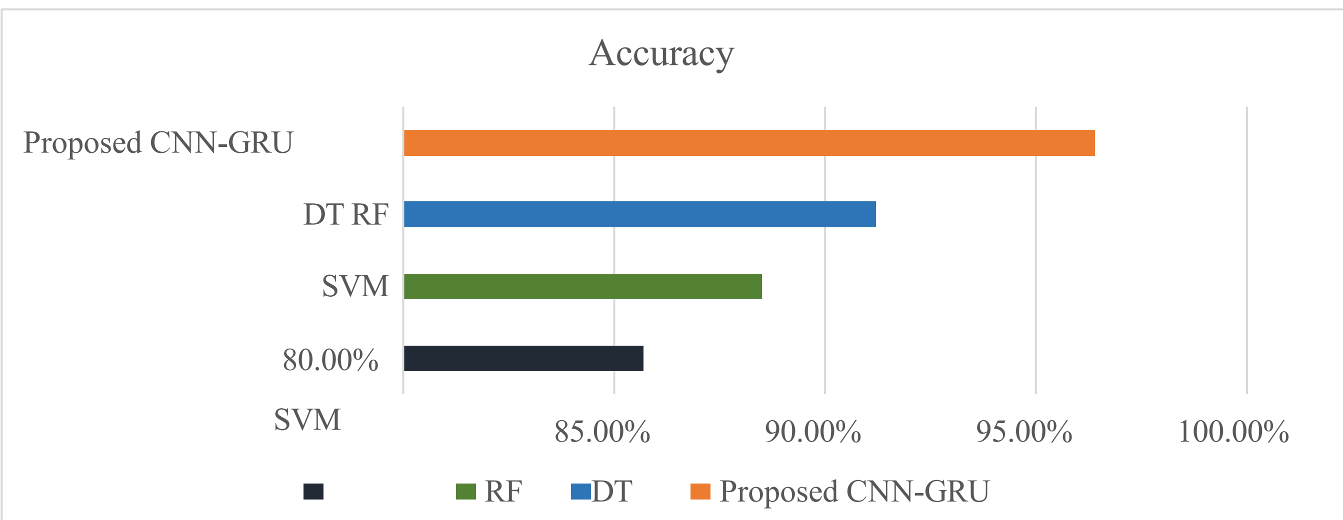


Figure 3 Illustrates Accuracy Performance

Figure 3 illustrates the comparative accuracy performance of four classification models: SVM, RF, DT, and the Proposed CNN-GRU model. Among all, the CNN-GRU model achieved the highest accuracy of 96.4%, significantly outperforming the traditional machine learning models. The DT followed with an accuracy of 91.2%, while RF and SVM recorded 88.5% and 85.7% respectively.

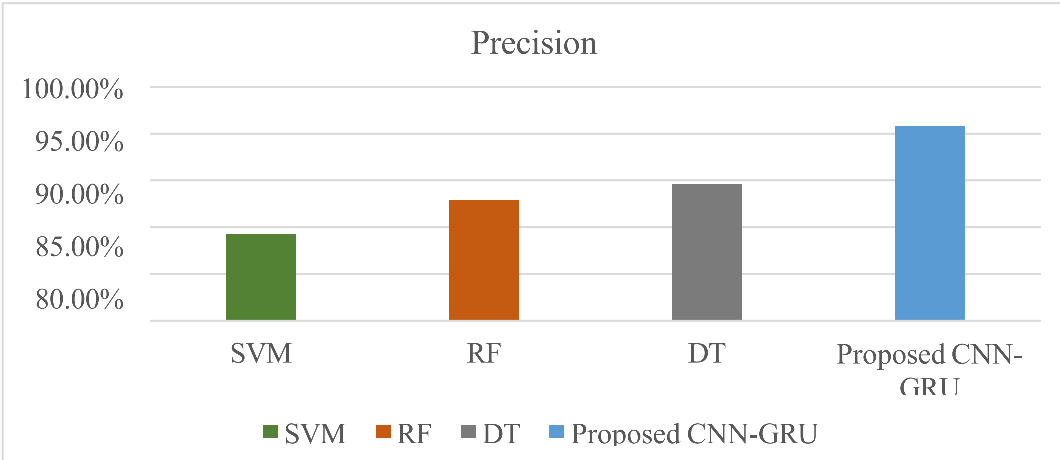


Figure 4 Illustrates Precision Performance

Figure 4 demonstrates the precision performance of four classification models: SVM, RF, and DT. The Proposed CNN-GRU achieved the highest precision of 95.8%, indicating its superior capability in minimizing false positives during classification. The Decision Tree and Random Forest models showed moderate precision values of 89.6% and 87.9%, respectively, while the SVM model recorded the lowest precision at 84.3%.

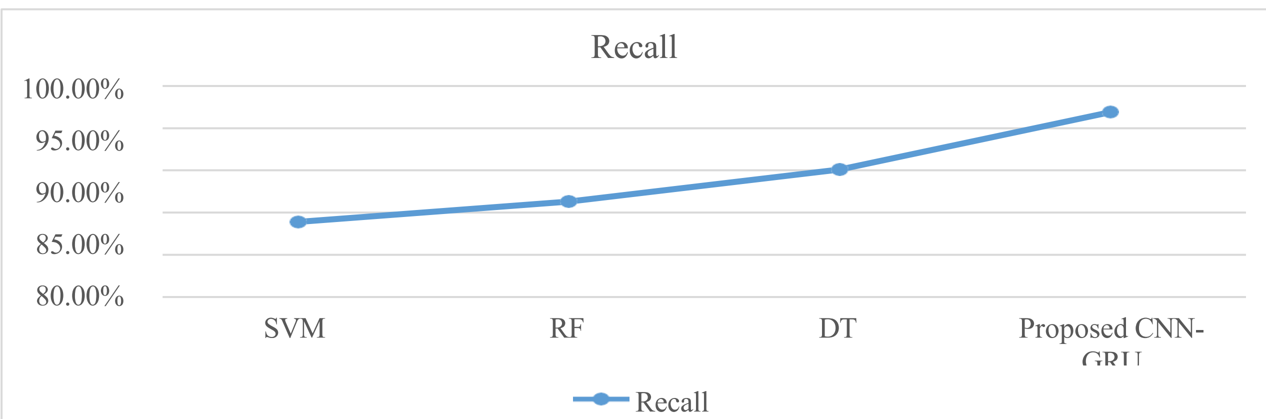


Figure 5 Illustrates Recall Performance

Figure 5 shows the recall ability of four classifiers: SVM, Random Forest, Decision Tree, and the Proposed CNN-GRU. The Proposed CNN-GRU has the highest value of recall at 96.9%, reflecting its high capability to accurately pick out pertinent instances with fewer false negatives. This is far greater compared to the Decision Tree (90.1%), Random Forest (86.3%), and SVM (83.9%).

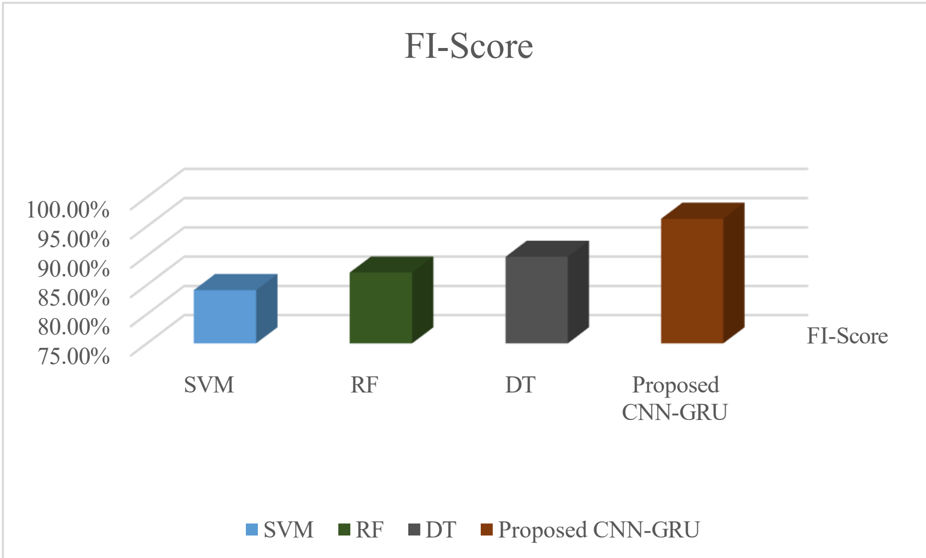


Figure 6 Illustrates FI-Score Performance

The F1-score value for the four models Decision Tree, Random Forest, Support Vector Machine, and Proposed CNN-GRU is shown in Figure 6. The CNN-GRU model captures the highest F1-score of 96.3%, which exceeds its balanced precision and recall capacities. This is higher than the Decision Tree (89.8%), Random Forest (87.1%), and SVM (84.1%). The high F1- score of the suggested model guarantees its resilience in processing real-time visual information,accurately detecting true positives even at the cost of reducing both false positives and false negatives.

## V. CONCLUSION

Lastly, the proposed AI-driven smart glass system is an extremely effective assistive system for blind and visually impaired users that employs advanced image processing, feature selection, and hybrid deep learning algorithms. Anisotropic Diffusion Filtering ensures high-quality pre- processed input and Particle Swarm Optimization optimizes efficiency and usability of feature selection. The hybrid CNN-GRU system exhibits superior performance in spatial as well as temporal comprehension, supporting precise real-time interpretation of the immediate surroundings. Test results, at a 96.4% accuracy, 95.8% precision, 96.9% recall, and 96.3% F1- score, confirm the system's reliability and robustness in object detection and obstacle recognition. This smart system greatly enhances mobility, safety, and independence for visually impaired users, making a tangible contribution to their quality of life and independence in traveling around complex spaces.

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