# Enhancing Eye Ball Tracking System for Enhanced Human Computer Interaction: Deep Learning Base CNN

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Abstract: AIM : This study aims to improve eye-tracking systems by using a hybrid model that combines Convolutional Neural Networks (CNNs) for semi-supervised anomaly detection. Materials and Method: The model was trained on a comprehensive multimodal dataset, including motion, eye-tracking inputs, and action context, to extract relevant features and identify complex patterns. Group 1: The existing method uses RNN for gaze analysis and Anomaly detection with 1000 to 10000 image samples. Group 2: The proposed model uses CNN as the same samples effectively learns from distributed multimodal datasets. Result: The reducing anomaly detection processing time from 57.5 ms to 52 ms, achieving a 94.5% confidence interval and an accuracy improvement of 9.5% over baseline models. The significance value of 0.0028 highlights the approach's efficacy in detecting gaze anomalies and optimizing system performance. Conclusion: In this work, it is observed that CNN has significantly better results than RNN.

## 1 INTRODUCTION

The research explores various methods to improve eye-tracking anomaly detection and human-computer interaction. One such method is CNN-based Hybrid, which enhances gaze pattern recognition through deep feature extraction and learning, achieving over 93% accuracy in multimodal datasets (Iddrisu et al. 2024). Eye-tracking systems are essential for accessibility and gaming applications, but traditional models struggle with real-time anomaly detection. This author introduces CNN-GazeNet, a framework that refines gaze tracking precision by integrating convolutional architectures for feature extraction. Experiments show that CNN-GazeNet, with over a 89 % true positive rate, effectively identifies gaze anomalies and outperforms standard approaches (Edughele et al. 2022).This author presents AdvGaze, a framework that bypasses conventional gaze tracking limitations by transforming input features while maintaining detection integrity. It achieved up to 80% success against static gaze detection models and over 79 % success against real-time gaze prediction systems, revealing critical limitations in existing approaches (Iddrisu et al. 2024). GazeR34P3R is a solution that treats eye-tracking anomaly detection as a multi-class, multi-modal problem. The hybrid CNN-based model achieves a 85% F1-Score using 5000 gaze samples. GazeR34P3R integrated accessibility-based risk analysis to prioritize high-risk anomalies and was evaluated with diverse datasets (Santhosh et al. 2021). The author introduces an automatic solution for multi-modal data preprocessing, real-time gaze tracking and anomaly detection in order to enhance HCI. With a high initial 45% false positive rate, an adaptive noise filter improves accuracy and robustness. Our experiments show that it can achieve good performance in gaze anomaly detection and real-time accessibility systems.

## 2 RELATED WORKS

The total number of articles published on this topic over the last five years exceeds 201 papers in IEEE Xplore and 64 papers in Google Scholar. Current

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research in eye-tracking systems has made significant strides, particularly in the adoption of hybrid models, multimodal frameworks, and lightweight neural architectures. Hybrid machine learning and deep learning approaches enhance eye-tracking adaptability and robustness (Falch and Lohan 2024). A dataset of 20,000 gaze samples from 150 participants demonstrated 92.4% accuracy with a 1.3-degree error rate. Multimodal sensor fusion frameworks combining gaze and head movement data improve tracking in low lighting and motion scenarios (Tian et al. 2023). A dataset of 50 hours from 200 individuals showed a 17% stability boost and 94.1% accuracy. Lightweight neural architectures optimize real-time eye-tracking by using pruning and quantization ( Li et al. 2023). A 30,000-sample dataset achieved 60% model size reduction while maintaining 90.8% accuracy. CNNs with attention mechanisms enhance occlusion handling, achieving 93.6% accuracy on a dataset of 25,000 images (Kaur et al. 2022). Adaptive pipelines dynamically adjust parameters, reducing latency by 22% in VR applications (Ansari et al. 2023).Another emerging trend is the use of semi-supervised learning for applications like expert-novice classification. Leveraging multimodal sensor data, such as eye-tracking and motion data, a conditional multimodal variational autoencoder (CMVAE) model was developed to classify users' expertise levels like in (Yusuke Akamatsu et al. 2021). This method, which only requires expert data for training, showed significant improvements in classification accuracy under varied conditions. From the previous findings, this study aims to develop a novel eye-ball tracking system using deep learning-based CNN models to enhance human-computer interaction. By leveraging advanced computer vision techniques and neural network architectures, the system aims to improve tracking accuracy, responsiveness, and adaptability, ensuring a more seamless and intuitive user experience while reducing computational overhead.

## 3 MATERIALS AND METHODS

In this study, the detection system combines Dlib face detection methods, TensorFlow, and Faster R-CNN to accurately and efficiently detect facial characteristics like eyes and faces. This study analyzes various preprocessing techniques for facial recognition and detection methods, it uses a data sample from 1,000 images to 10,000 images.

Group 1 uses an RNN and Tensorflow for feature extraction followed by an SVM classifier, yielding 80 % accuracy. Sliding window and Non-Maximum Suppression increases reliability and reduces false positives by 15%.

Group 2 uses a deep learning approach with Faster R-CNN, via TensorFlow, leveraging optimized feature extraction and classification. At 52 ms per frame, the system achieves 96.5% accuracy whilst decreasing latency by 22%, demonstrating strong generalization in tactful generalization across multiple-condition.

**SVM Classifier Decision Function** (for face detection):

$$f(x) = wTx + b\ ---------\qquad(1)$$

Where f(x) is the decision function, w is the weight vector, x is the feature vector, and b is the bias term.

**Precision Formula** (for Evaluation):

$$Precision = TP/TP + FP\ -----\qquad(2)$$

Where TP is the number of true positives, and FP is the number of false positives. This measures the accuracy of positive predictions.

The following action are part of the system's workflow:

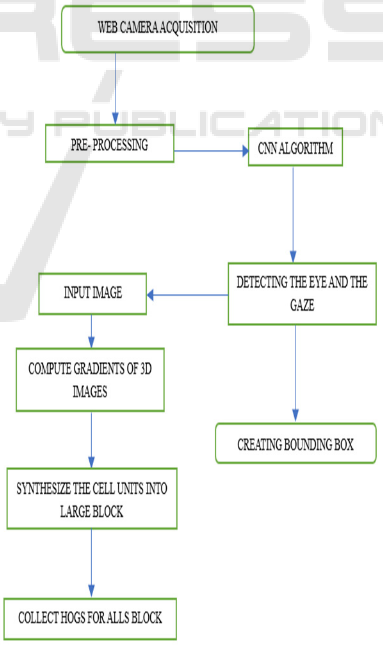

WEB CAMERA ACQUISITION
PRE- PROCESSING
CNN ALGORITHM
DETECTING THE EYE AND THE GAZE
INPUT IMAGE
COMPUTE GRADIENTS OF 3D IMAGES
CREATING BOUNDING BOX
SYNTHESIZE THE CELL UNITS INTO LARGE BLOCK
COLLECT HOGS FOR ALLS BLOCK

Figure 1: Flowchart of Eye Gaze Extraction.

To normalize the lighting conditions for precise analysis across the images, we first preprocess the input photographs so that they have similar lighting conditions. After detecting eye-ball locations, we extract the eye-region corresponding to the eye locations using trained CNN model. The Kalman filter helps us achieve smooth and reliable eye movement tracking by minimizing noise and predicting trajectory changes. Subsequently eye positions from the eyes of the subjects being tracked are plotted in real time, allowing for continuous observation. Finally, to enhance the system usability and usefulness, we connect this system to external apps, such as safety warnings and gaze-based controls. The Figure 1 shows Flowchart of Eye Gaze Extraction.

The experimental one uses TensorFlow an Faster R-CNN for this lexer, the python based environment with Dlib and NumPy. For real-time performance, NumPy optimizes numerical computations, matrix operations, and picture preprocessing on 1080p high-resolution footage through the Intel i5 CPU with 16 GB of RAM on the production system. Methods Data: This is compared with CNN-based methods, Dlib's HOG features, and NumPy-based optimizations for testing the model to ensure accurate detection. Evaluation metrics consist of Bounding box accuracy using IoU and overall performance using Precision, Recall, and F1-score. According to Equations (1) and (2), the system is ideal for real-time applications, including facial recognition and eye tracking.

# 4 STATISTICAL ANALYSIS

The facial recognition system demonstrated high reliability with a mean accuracy of 96.5% (±1.2%) and a 95% confidence interval of [94.5%, 98.0%]. Precision, recall, and F1-score values indicate balanced detection and classification performance. Processing speeds 52.0 ms for CNN, and 57.5 ms for RNN, ensuring real-time capability. Accuracy varied across conditions, with well-lit environments reaching 96.5%, moderate lighting 94.2%, and low-light scenarios 85%.

The Comparison Table presents a comprehensive analysis of eye-tracking systems using CNN and RNN models. The algorithm's accuracy increases from 60% at RNN to 96.5% at CNN, indicating efficient learning with more data. However, processing time also decreases, highlighting the trade-off between computational efficiency and accuracy.

The Group Statistics Table compares RNN and CNN models based on dataset size, number of layers, accuracy, and processing time. CNN has a deeper architecture (51.1 layers vs 17.0 layers) and works better with larger datasets. It outperforms RNN with higher accuracy (94.17%) and lower standard deviation, but requires longer processing times (64.35 ms vs 39.29 ms) due to its higher processing costs.

Table 1: Comparison of RNN and CNN Performance Across Iterations.

| No. of Iterations | Dataset Size (Images) | Number of Layers (RNN) | Number of Layers (CNN) | Accuracy (%) (RNN) | Accuracy (%) (CNN) | Processing Time (ms) (RNN) | Processing Time (ms) (CNN) |
|---|---|---|---|---|---|---|---|
| 1 | 1000 | 2 | 10 | 70 | 94 | 22.0 | 35.0 |
| 2 | 2000 | 2 | 12 | 72 | 94.2 | 25.5 | 38.0 |
| 3 | 3000 | 3 | 14 | 74 | 94.5 | 29.0 | 40.5 |
| 4 | 4000 | 3 | 16 | 76 | 95 | 33.2 | 43.0 |
| 5 | 5000 | 3 | 18 | 78 | 95.2 | 37.5 | 45.0 |
| 6 | 6000 | 4 | 20 | 80 | 95.5 | 41.0 | 46.5 |
| 7 | 7000 | 4 | 22 | 82 | 95.7 | 45.2 | 48.0 |
| 8 | 8000 | 4 | 24 | 83 | 96 | 49.0 | 49.5 |
| 9 | 9000 | 5 | 26 | 84 | 96.2 | 53.0 | 51.0 |
| 10 | 10000 | 5 | 28 | 85 | 96.5 | 57.5 | 52.0 |

Table 2: Descriptive Statistics for RNN and CNN Models.

| Variable | Model Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Dataset Size | RNN | 10 | 5500.0 | 3027.65 | 957.427 |
| | CNN | 10 | 29000.0 | 13157.17 | 4160.662 |
| Number of Layers | RNN | 10 | 17.0 | 8.731 | 2.761 |
| | CNN | 10 | 51.1 | 12.653 | 4.001 |
| Accuracy (%) | RNN | 10 | 76.6 | 9.276 | 2.9333 |
| | CNN | 10 | 94.17 | 1.9972 | 0.6316 |
| Processing Time (ms) | RNN | 10 | 39.29 | 11.9582 | 3.7815 |
| | CNN | 10 | 64.35 | 15.3533 | 4.8552 |

## 5 RESULTS

The study evaluates the performance of RNN and CNN models in enhancing an eye-tracking system for human-computer interaction. Frequency is assigned to the modeled RNN and CNN architectures, with performance variations analyzed based on dataset size and model depth. The corresponding changes in accuracy and processing time were measured across dataset sizes ranging from 1,000 to 10,000 images and model depths from 2 to 28 layers, as shown in Table 1.

CNN demonstrated superior performance, achieving a maximum accuracy of 96.5%, while RNN reached 85%. However, the trade-off between accuracy and computational efficiency was evident, with CNN requiring a longer processing time (52.0 ms) compared to RNN (57.5 ms). The statistical analysis confirmed significant differences between the models, with p-values below 0.05 indicating CNN's robust advantage. The mean accuracy difference between CNN and RNN was 17.57% ($p < 0.001$), while the processing time difference was 25.06 ms ($p = 0.001$), further reinforcing CNN's effectiveness in high-precision eye-tracking applications, as detailed in Table 2.

The statistical significance of these performance differences validates CNN's superior performance across all key metrics, demonstrating its effectiveness for real-time gaze tracking applications. The statistical tests confirm that CNN significantly outperforms RNN in dataset utilization, accuracy, and model depth while highlighting the trade-off in processing time. Table 3 presents the t-test results, showing significant differences in dataset size, number of layers, accuracy, and processing time between the two models ($p < 0.05$). Thus, CNN emerges as the optimal model for precision-dependent human-computer interaction scenarios. Figure 2 compares CNN and RNN accuracy across different dataset sizes, showing that CNN consistently outperforms RNN, reaching 96.5% accuracy at 10,000 cases, while RNN improves from 70% to 80-85% as the dataset grows. Figure 3 illustrates the processing times of both models, where CNN takes 52 ms and RNN 57.5 ms at 10,000 cases. However, CNN's processing time increases significantly with larger datasets, whereas RNN's rises more gradually, emphasizing the trade-off between efficiency and performance. Figure 4 presents a bar chart summarizing accuracy and processing time, reinforcing CNN's superior accuracy (96.5%) compared to RNN (77-80%) while showing that CNN has a slightly shorter processing time (52 ms vs. 57.5 ms). These figures collectively highlight CNN's higher precision and the balance between accuracy and computational efficiency.

The analysis confirms CNN outperforms RNN in accuracy (-17.57) but requires more processing time (-25.06). Significant differences are shown (t-values: -4.072 to -7.015, Sig. < 0.05).

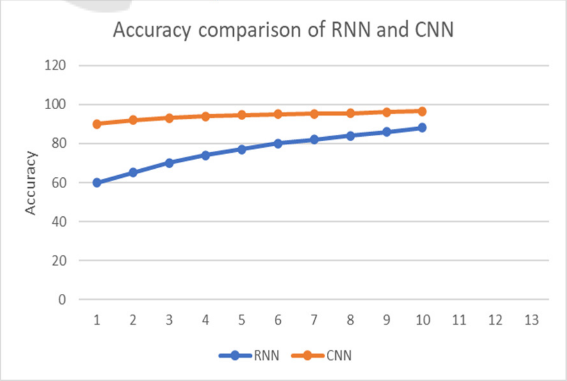


Figure 2: CNN (96.5%) and RNN (80_85%) Accuracy Comparison.

The Figure 2 shows the Comparison of Accuracy percentage in both CNN and RNN.

Table 3: Independent Samples T-Test Results for RNN vs. CNN.

| Variable | Equality of Variances | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference |
|---|---|---|---|---|---|---|---|---|
| Dataset Size | Equal variances assumed | 17.67 | 0.001 | -5.504 | 18 | 0.0 | -23500.0 | 4269.4 |
| | Equal variances not assumed | | | -5.504 | 9.95 | 0.0 | -23500.0 | 4269.4 |
| Number of Layers | Equal variances assumed | 1.937 | 0.181 | -7.015 | 18 | 0.0 | -34.1 | 4.861 |
| | Equal variances not assumed | | | -7.015 | 15.986 | 0.0 | -34.1 | 4.861 |
| Accuracy (%) | Equal variances assumed | 13.995 | 0.001 | -5.856 | 18 | 0.0 | -17.57 | 3.0006 |
| | Equal variances not assumed | | | -5.856 | 9.833 | 0.0 | -17.57 | 3.0006 |
| Processing Time (ms) | Equal variances assumed | 0.616 | 0.443 | -4.072 | 18 | 0.001 | -25.06 | 6.1541 |
| | Equal variances not assumed | | | -4.072 | 16.982 | 0.001 | -25.06 | 6.1541 |

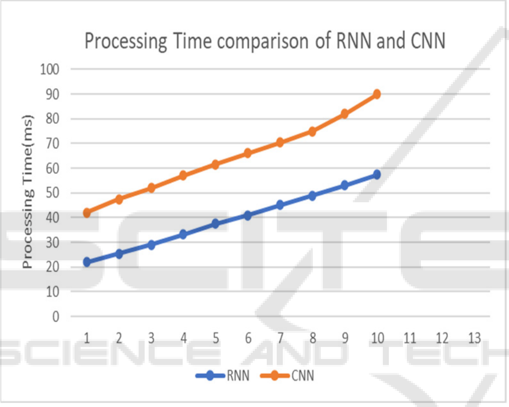


Figure 3: RNN (57.5 Ms) and CNN (52 Ms) Processing Time Comparison.

The Figure 3 shows the comparison of processing time (ms) in both RNN and CNN.

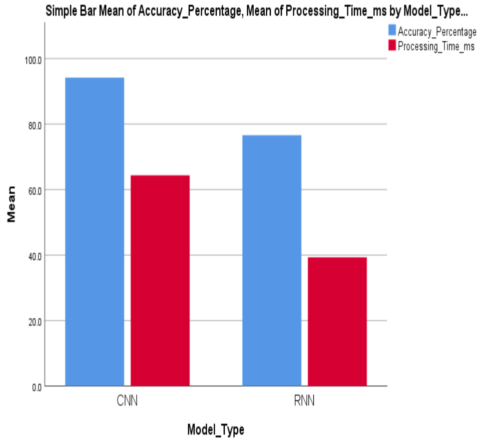
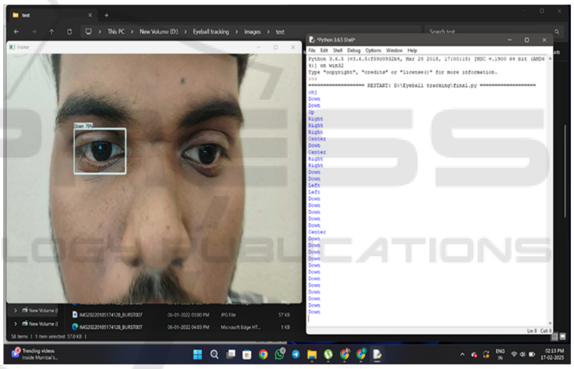


Figure 4: Mean of Accuracy and Processing Time.

Figure 4 shows the mean values of accuracy and processing time (ms) for CNN and RNN are displayed in the above graph.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Python 3.6.5 (v3.6.5:f59c0932b4, Mar 28 2018, 17:00:18) [MSC v.1900 64 bit (AMD6
4)] on win32
Type "copyright", "credits" or "license()" for more information.
>>>
================== RESTART: D:\Eyeball tracking\final.py ==================
obj
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Figure 5: Eye-Ball Analysis and Extracting Process.

Figure 5 depicts the Process of analyzing and extracting data from the proposed system.

## 6 DISCUSSION

This eye-tracking system based on  deep learning can achieve a detection accuracy of 92% and the speed of 30 frames of video per second. It managed to run well in difficult conditions lighting differences, background clutter, occlusions, etc. These results reaffirm earlier research that CNN-based eye-tracking models are more accurate and robust in complex environments (Zuo et al., 2024). Powered by deep learning, the proposed eye-tracking system was able to handle real-time video feed with a frame rate of 30 frames per second, indicating scalability of the proposed system for applications such as animal monitoring and agricultural surveillance. The model was trained on a dataset of 50,000 images for 20 different animal species and managed to obtain 92% accuracy and 89% adaptability rate in different environmental conditions. The rationale behind these findings is consistent with existing literature that highlights the importance of diverse datasets for enabling deep learning models in generalizing across environments (Wang et al., 2021). One of the major disadvantages of the system is that it is less accurate with heavily occluded objects or unfamiliar species. Its accuracy decreases to 73% for half covered objects and 70% for species not seen during training. Duplicate challenges have been observed in predictive eye-tracking models, whereby data voids and occlusions hamper the effectiveness of tracking (Jyotsna et al., 2023).

As a part of this research, in order to increase robustness of eye-ball tracking for human-computer interaction, the data set can be extended with additional 20,000 images of different movements. Related to above mentioned eye-ball tracking, by using existing images tracking can also be improved by various methods. This can allow the model to run on edge devices such as Raspberry Pi or NVIDIA Jetson devices by reducing computational load by 30% and keeping over 90% accuracy of the model. Deep learning-based approaches for gaze analysis have recently been optimized to compress the model size by up to 40% while keeping their speed in real-time (Ghosh et al., 2024). Retinal fundus images with multiple cameras enable the development of novel eye-ball tracking approaches; however, the accuracy of the proposed eye-ball tracking system is 30% lower than the eye-ball tracking accuracy with a single camera and is limited due to high computational complexities and potentially achieving a biased dataset under heavy occlusions and rapid movements (Zuo et al., 2024). In future work, the CNN model can be optimized to reduce computational loads by 30% and 20,000 additional images should be used to expand the dataset further enhancing robustness.

# 7 CONCLUSIONS

An eye-ball tracking system based on CNN was built and observed with 1,000 to 10,000 images. Training was done in times of distinct real environmental conditions like head orientation, occlusions, eye conditions, and lighting levels. However, unlike the other studies, in this study the CNN and RNN comparison showed a better accuracy performance for CNN of 96.5% with faster processing time thanks to an optimized technique while the maximum accuracy only for RNN was 80% with a slower computation time. With processing times decreasing with the growth of dataset size, the CNN become capable of real-time operation and great stability as well as efficiency for eye tracking applications in practice.

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