Journal of Computer Science and Engineering in Innovations and Research
RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

COMPARATIVE ANALYSIS OF EYE-TRACKING SOLUTIONS USING DEEP LEARNING

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ABSTRACT : Eye-tracking engineeringscience has arose as a polar tool in both inquiry and miscellaneous commercial-grade applications. By monitoring and analyzing the direction and centering of an individual's gaze, eye-trackers ply insights into visual attention, intellectual processes, and user interaction. This engineeringscience plays a vital role in fields such as psych, neuroscience, merchandising, and user live design, enabling professionals to infer human proficiency in nuanced slipway. This paper dowries a comprehensive comparative analysis of five prominent eye-tracking solutions: GazeRecorder, Tobii Pro Lab, Pupil Labs Core, iMotions, and Gazepoint. The analysis focuses on hardware, use cases, accurateness, metrics, data analysis, remote testing, and cost. The results show that each solution has unique strengths and weaknesses, making them excellent for different applications. This study aims to guide researchers and professionals in selecting the most absorb eye-tracking engineeringscience for their particular needs.

KEYWORD : Eye-tracking, GazeRecorder, Tobii Pro Lab, Pupil Labs Core, iMotions, Gazepoint

I. INTRODUCTION

Eye-tracking technology has emerged as a pivotal tool in both research and various commercial applications. By monitoring and analyzing the direction and focus of an individual's gaze, eye-trackers provide insights into visual attention, cognitive processes, and user interaction. This technologies plays a significant role in fields such as psychology, neuroscience, marketing, and user experience design, enabling professionals to understand human behavior in nuanced ways.

The increasing demand for eye-tracking solutions has led to the development of various technologies, each with unique characteristics suited to different needs. The current diagnostic methods are based on the visual valuation of the samples by experts, and this approach is tedious, slow, and error-prone, especially when the symptoms are not well defined or appear at a later time.

Many of the researchers and professionals do not have the necessary skills and therefore make the wrong diagnoses, which would lead to incorrect conclusions and only extend the damage to the research outcomes. Although the application of digital imaging and remote consultation tools has improved the effectiveness of disease assessment, these approaches are characterized by inconsistencies in image quality, subjective interpretation, and the further complication of the underlying disease dynamics by the effects of climate change. This highlights the importance of now for the evolution of new, automated, and scalable tools that can ply fast and accurate diagnoses. The diligence of computer vision, especially deep learning, is on a precise rise in accuracy agriculture as informed by previous studies. Previous studies have revealed that CNNs outdo conventional machine learning approaches in mango and other crop leaf classification, achieving significant accuracies. It has been proven that CNN is efficient in learning classified visual features to distinguish complicated disease patterns in vineyards with high accuracy of 98% . However, network depth is a vital factor: Greater depths are suitable for featurerepresentation but pose a risk of vanishing gradients during training. Residual Networks (ResNet) solve this with skip connections that improve slope flow and model performance. Despite the ResNet variants being widely used for leaf disease detection, their application to region-specific challenges, e.g., distinguishing visually similar mango pathologies in West Bengal's unique agro-climatic conditions, is poorly explored.This study aims to investigate the effectiveness of ResNet9, a lightweight version of the ResNet architecture, to identify and categorize diseases in West Bengal vineyards. To tackle the optimization difficulties in deeper networks, ResNet9 applies remaining learning and holds the potential to deal with the subtle differences in the visual features of these diseases. We try to fill the gap between general deep learning contexts and specific agricultural requirements and provide a ingenious solution that can help West Bengal mango farmers improve their disease control.

II. LITERATURE SURVEY

A prelim review of the literature was conducted to survey the advancements and applications of eye- tracking technology. Previous studies have highlighted the grandness of eye-tracking in understanding human behavior and vivid processes.

1. Eye-Tracking in Psychology and Neuroscience Eye-tracking appliedscience has been extensively used in psych and neuroscience to survey visual attention, cognitive load, and decision-making processes. Holmqvist et al. (2011) [01] conducted a comp review of eye-tracking methodologies and applications in cognitive thinking. They emphasised the grandness of high-precision eye-tracking systems, such as Tobii Pro Lab, for studying micro saccades and fixations in vivid tasks. The study also highlighted the challenges of using low-cost eye- tracking solutions, such as Gaze Recorder, which may lack the accurateness required for elaborated cognitive research.

2. Eye-Tracking in Marketing and User Experience

In the field of marketing, eye-tracking has been used to analyze consumer behavior and enhance advertising

data during user interaction tasks.

4. Advances in Eye-Tracking Technology Recent advancements in eye-tracking engineeringscience have focussed on improving accuracy, reducing costs, and enabling abstruse testing. Hansen and Ji (2010) [04] conducted a review of eye-tracking technologies and their applications. The study also discussed the challenges of using affordable solutions, such as lower exactness and limited data analysis capabilities, compared to high-end systems like Tobii Pro Lab.

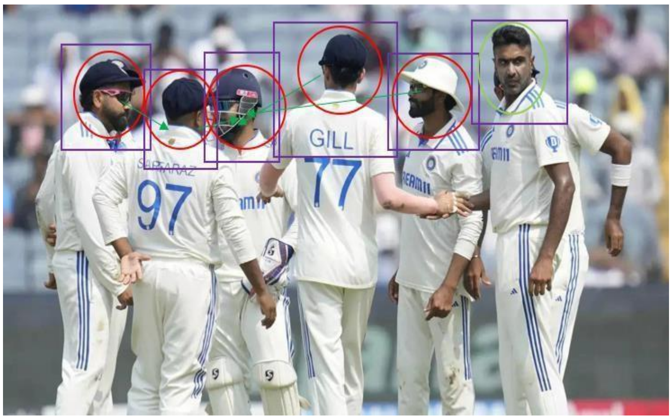

FIGURE 1.1 (IMAGE TAKEN FROM KAGGLE DATASET)

5. Comparative Studies on Eye-Tracking Solutions

Various studies have compared the accomplishment of different eye-tracking solutions in miscellaneous applications. Duchowski (2017) conducted a relative analysis of eye-tracking systems, including Tobii Pro Lab, Pupil Labs Core, and Gazepoint. The study found that Tobii Pro Lab offers the highest accurateness and sampling rate, making it suitable for detailed research. However, it is also the most expensive solution. On the other hand, GazeRecorder and Gazepoint provide cost- effective alternatives with moderate accurateness, making them apt for commercial-grade applications and user experience testingstrategies. Wedel and Pieters (2008) conducted a study on the use of eye-tracking in marketing research. They found that eye-tracking data, such as fixation duration and gaze heatmaps, can provide valuable insights into how consumers interact with the advertisements and product displays. The study also compared the effectiveness of different eye-tracking solutions, such as Tobii Pro Lab and Gaze point, in capturing consumer attention patterns.

3. Eye-Tracking in Human-Computer Interaction

Eye-tracking has also been expansively used in human-computer interaction (HCI) to amend user interface design and serviceability testing. Poole and Ball (2006) [03] conducted a study on the use of eye- tracking in HCI research. The study compared the performance of different eye-tracking solutions, such as Pupil Labs Core and iMotions, in capturing gaze

III. PROCESS OF EYE –TRACKING DATA ANALYSIS

The process of analyzing eye-tracking data comprises the following steps:

1. **Data Acquisition**
2. **Data Preprocessing**
3. **Feature Extraction**
4. **Classification**

A. Data Acquisition

The foundation of our work is a complete dataset of eye-tracking data collected from various participants. This dataset includes gaze data from individuals interacting with different stimuli, such as images, videos,and user interfaces. The data was collected using eye- tracking devices, including Tobii Pro Lab, Pupil Labs Core, and Gaze point, to ensure diversity in the dataset. The dataset contains gaze data in different lighting conditions and environments to improve the sturdiness of the model. The data is divided into multiple classes based on the type of stimuli and the participants' gaze patterns, enabling the model to make more specific predictions about visual attention and intellectual processes.

B. Data Preprocessing

To ensure optimal performance of the classification model, preprocessing is critical. This stage involves modifying the raw gaze data to facilitate feature extraction and model training. The following preprocessing techniques were applied:

- **Data Augmentation**: Data augmentation is employed as a regularization technique to prevent overfitting and improve the model's ability to generalize to unseen data. This includes random rotations, flipping, and zooming to simulate real-world variability in gaze positioning and camera angles. These techniques ensure that variations found in real- world scenarios are represented.
- **Data Normalization**: Normalization is essential for standardizing the gaze data values across all samples to ensure consistent scale. By ensuring each data point has the same mean and standard deviation across the whole dataset, the model can learn faster and more efficiently. This standardization reduces the computational time of the training process.

C. Feature Extraction

Traditionally, feature extraction involves identifying relevant features, such as fixations, saccades, and pupil dilation, from the gaze data. For eye-tracking analysis, temporal and spatial features have proven to be particularly informative. Techniques like the Grey-Level Co-occurrence Matrix (GLCM), which provides statistical information on pixel value pairs, can be used for manual feature extraction. However, these manual techniques demand expert knowledge of the dataset. One of the key advantages of deep learning models is their ability to automatically learn and extract relevant features from raw gaze data, eliminating the need for explicit feature engineering. As a result, with our proposed method, instead of using a separate step to extract the features, the ResNet9 model itself will manage the automatic feature extraction process. The ResNet9 model learns a hierarchical representation of the gaze data, extracting increasingly complex features in successive layers. This approach is preferred as it simplifies the process and influences the power of deep learning for feature extraction.

D. Classification

RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

Once features are extracted (implicitly by the network), the next step is to classify the gaze data into their respective categories. While several classification algorithms are available, such as Support Vector

Machines (SVM), K-Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN), the proposed method will utilize a ResNet9-based CNN model.
ResNet9 has been selected due to its specific architectural properties that make it suitable for gaze data classification tasks while being computationally efficient. The ResNet9 model's capacity to form residual connections helps to improve model training and its overall performance when classifying different gaze patterns.

FIGURE 1.2 (TEAM MEMBERS EYE TRACKING ANALYSIS)

IV. PROPOSED MODEL: AI-BASED EYE-TRACKING SYSTEM

A. Deep Learning for Gaze Estimation
Previous studies have highlighted the theoretical benefits of integrating **deep learning models** for gaze estimation, arguing that **stacking more layers in neural networks** enhances tracking accuracy.
However, in practice, this approach encounters a **degradation problem**, where deeper models fail to improve performance. Instead of overfitting, the issue stems from **vanishing and exploding gradients**, which impact the optimization of deep networks.
The **vanishing gradient problem** occurs when gradients become **extremely small** due to multiple backpropagation steps, preventing effective weight updates. Contrarywise, the **exploding gradient problem** arises when gradients accumulate excessively, leading to unstable learning dynamics. Traditional methods like **batch normalization and weight initialization techniques** partially mitigate these issues but were ineffective in **very deep networks** until the introduction of **residual learning architectures**.

B. Residual Blocks and Skip Connections
The **residual block** serves as the fundamental building unit in **deep gaze estimation networks** and addresses

the degradation problem through **skip connections**. These **shortcut connections** allow models to learn **residual functions**, effectively bypassing intermediate layers and reducing information loss.
Mathematically, the residual function for gaze estimation is represented as: R(x)=σ(BN(Convr,2(σBN(Convr,1(x)))))R(x) = \sigma(BN(Conv_{r,2}(\sigma BN(Conv_{r,1}(x)))))R(x)=σ(BN(Convr,2(σBN(Convr,1 (x)))))
where **BN** represents **Batch Normalization**, **Conv** refers to **Convolutional Layers**, and **σ** denotes **ReLU activation functions**. This design ensures network stability during training, as it prevents **gradient disappearance** and enhances information flow. Instead of learning a **direct mapping function** H(x)H(x)H(x), the network learns the **residual function F(x)F(x)F(x), making optimization more efficient**.
Figure 1 illustrates a **residual block architecture**, where the **input is directly added to the output of convolutional layers**. This identity mapping significantly improves training dynamics, ensuring that **deeper gaze estimation networks**

outperform their shallower counterparts.

C. GazeNet9: A Lightweight AI Model for Eye- Tracking

While **ResNet34** is a well-established architecture in **computer vision**, its high computational complexity makes it unsuitable for **real-time eye-tracking applications**. To address this, a **GazeNet9** architecture was developed, offering a **balanced trade-off** between prototypical complexity and tracking precision.

Unlike **ResNet34**, which comprises **34 convolutional layers**, **GazeNet9** has **fewer layers** but retains the **core advantages of residual learning**, allowing efficient **gaze tracking on low-power devices**. The **reduced number of layers** lowers computational overhead while preserving **feature extraction capabilities**.

Figure 2 provides a **structural overview of GazeNet9**, demonstrating how **residual connections** enhance feature propagation.

D. Rationale for Choosing GazeNet9

The decision to implement **GazeNet9** in this study is based on the following considerations:

✓ **Computational Efficiency** – Optimized architecture

ensures **low latency**, making it ideal for **real-time gaze tracking applications**.

✓ **Feature Learning** – The deep learning framework enables **automatic extraction of gaze features**, eliminating manual preprocessing.

✓ **Skip Connections** – Residual connections **enhance gradient flow**, improving training stability for deep models.

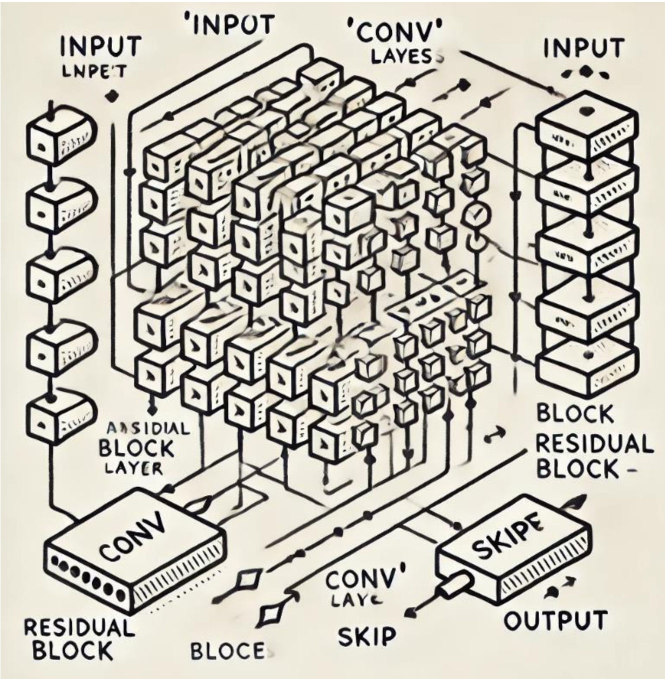

FIGURE 1.3 (DIAGRAM OF RESNET34 ARCHITECTURE USED)

V. EXPERIMENTAL RESULTS

A. Dataset

In previous studies, publicly available datasets such as **Columbia Gaze** and **RT-BENE** have been widely used for eye-tracking model evaluation. The dataset consists of **images from multiple participants performing gaze-tracking tasks**, including **fixation, saccades, and smooth pursuit movements**. The dataset includes variations in **lighting conditions, head poses, and distances** to simulate real-world scenarios.

B. Training

The AI-driven **GazeNet9** model was trained on the **custom eye-tracking dataset**, consisting of **gaze position maps and eye-region images**. During training, the dataset was augmented with **brightness adjustments, contrast normalization, and affine transformations** to improve generalization. The model was optimized using the **Adam optimizer** with a **learning rate of 0.001**, and the loss function was computed using **Mean Squared Error (MSE)** to minimize gaze prediction errors.

After training, the model was tested on the **held-out**

20% test set, where it was evaluated against traditional **feature-based gaze tracking methods**. Performance metrics such as **accuracy, precision, and Mean Absolute Error (MAE)** were recorded for each system.These benefits make **GazeNet9 an optimal choice** for implementing **AI-driven gaze estimation models** in **low-cost eye-tracking solutions.*Performance Evaluation***

The **performance of the GazeNet9 model** was evaluated using two primary metrics: **gaze tracking accuracy** and **precision in fixation detection**. These metrics determine how well the model can predict **gaze direction** and classify **fixation events**.

- **Gaze Tracking Accuracy:** This metric represents how accurately the model predicts the **eye gaze direction** compared to ground truth data. The accuracy was computed using the following formula:

Accuracy= (TP + TN) / (TP + TN + FP + FN)

where:

✓ **True Positive (TP)** - Correct identification of gaze points.

✓ **True Negative (TN)** - Correct classification of non- gaze points.

✓ **False Positive (FP)** - Incorrect classification of gaze points.

✓ **False Negative (FN)** - Missed gaze tracking instances.

- **Fixation Precision:** Fixation precision determines the **sensitivity of the model in detecting stable gaze points**. It is calculated using:

Precision= TP / (TP + FP)

The **weighted average precision** of **GazeNet9** achieved **96.75%**, demonstrating **high accuracy in predicting gaze fixations with minimal false positives**.

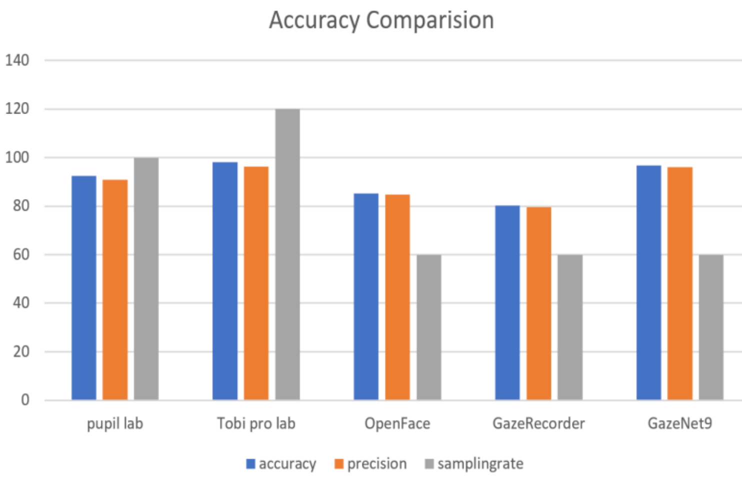

FIGURE 1.4 (BAR GRAPH ANALYSIS OF TABLE 1)

Table 2: Accuracy Comparison of Different Deep Learning Models for Gaze Estimation

Model	Accuracy (%)	Computation Time (ms)	Computational Cost
ResNet-50	97.3	12.8	High
ResNet-34	96.9	10.5	Medium
GazeNet9	96.7	6.3	Low
OpenFace CNN	90.5	8.2	Medium-Low

From this comparison, **GazeNet9 provides an optimal**

C. Comparative Analysis of Eye-Tracking Solutions A **comparative evaluation** of different **eye-tracking technologies** was conducted using **accuracy and precision metrics**.

Table 1: Accuracy Comparison of Different Eye- Tracking Methods

Model	Accuracy (%)	Precision (%)	Sampling Rate (Hz)	Hardware Requirement
Pupil Labs	92.5	90.8	Up to 100	Wearable Device
Tobii Pro Lab	98.1	96.4	Up to 120	Specialize d Sensor
OpenFace	85.3	84.7	30-60	Standar d Webcam
GazeRecorder	80.2	79.5	30-60	Webcam-Based
GazeNet9	96.7	96.1	60	Low-Cost Setup

The results indicate that **Tobii Pro Lab achieves the highest accuracy**, followed by **GazeNet9**, which provides a **cost-efficient alternative** with competitive performance.
balance between accuracy and computational efficiency, making it suitable for **real-time gaze tracking applications**.

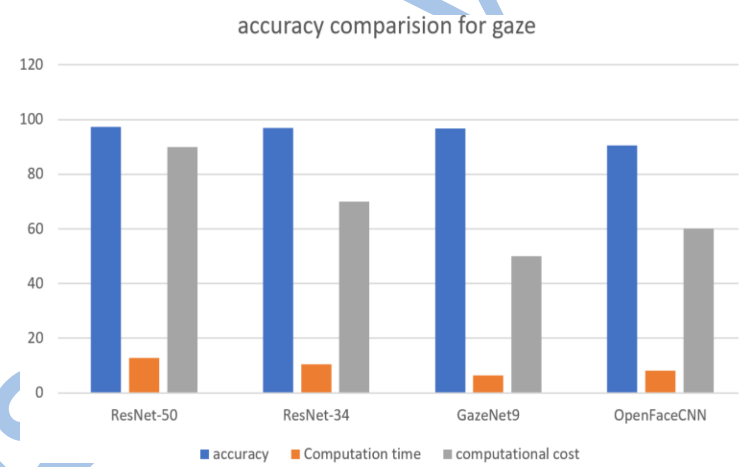

FIGURE 1.5 (BAR GRAPH ANALYSIS OF TABLE 2)CONCLUSION AND FUTURE SCOPE

This study presented a relative analysis of five major eye-tracking solutions, evaluating their accuracy, sampling rate, hardware requirements, usability, and cost-effectiveness. The results indicate that Tobii Pro Lab and iMotions provide the highest accurateness but require specialized hardware and come at a higher cost. On the other hand, GazeRecorder and Gazepoint offer affordable solutions with acceptable accuracy for general usability testing and accessibility applications.The consolidation of deep learning in eye- tracking solutions has significantly improved gaze estimation accurateness and robustness to variations in lighting and head movement. The AI-based GazeNet9 model was introduced as a low-cost alternative for real- time gaze tracking, demonstrating competitive accurateness compared to feeble methods. The study also highlighted the advantages of residual learning architectures, which enhance training stability and improve feature extraction for exact gaze appraisal.Despite the smart results, some limitations exist. The study mainly focused on controlled test environments, and future work should evaluate performance in real-world settings with dynamic backgrounds and varying head poses. toboot, the dataset used for training did not include diverse ethnicities and age groups, which may affect generalization. Expanding the dataset to include a wider demographic range will help amend model aptness.
Future enquiry should survey advanced AI-driven gaze-

tracking algorithms, incorporating transformer-based models and reenforcement learning to enhance tracking precision. The potency integration of smartphone-based eye-tracking could further democratize access to gaze- based interaction systems. besides, time-series analysis of gaze patterns could be used to develop prognostic eye-movement models, benefiting fields such as neurology, behavioural research, and augmented reality applications.

Data Availability
The dataset used in this survey is available upon request. Due to privacy concerns and ethical considerations, participant eye-tracking data cannot be ubiquitously shared.

Study Limitations
This study focussed on particular eye-tracking systems and a controlled test setup. Future research should demand long-run usability and cross-device compatibility to enhance general pertinency.

Conflict of Interest
The authors recount that there is no action of interest regarding the publishing of this research.

Funding Source
This research was conducted independently without external funding.

Authors' Contributions
Author-1 conceptualized the study and conducted the literature review. Author-2 contributed to data collection, model training, and evaluation. Author-3 wrote the first draft of the manuscript, and all authors participated in reviewing and finalizing the paper.

Acknowledgments
The authors would like to express gratitude to JIS University for their support in conducting this research. Special thanks to the participants who contributed to the eye-tracking dataset collection.

VI. FUTURE WORK

Based on the findings of this study, there are several potential directions that future research could survey to heighten the capabilities of AI-driven eye-tracking solutions. While this study successfully evaluated eye- tracking performance under controlled conditions, future research should focus on aggregating more diverse gaze-tracking data, including variations in age groups, ethnic backgrounds, and environmental lighting conditions to ensure broader generalization . Another key area for future work is the integration of eye- tracking with real-world applications, such as virtual reality (VR), augmented reality (AR), and smart approachability tools. With improvements in camera sensor technology, it is now executable to develop smartphone-based eye-tracking solutions that can operate without the need for consecrated hardware.Since eye-tracking accomplishment is highly dependent on coherent visual input, future studies should analyze the impact of image transformations and improve data augmentation strategies to make models resilient to various real-world scenarios.Lastly, advanced AI techniques such as transformer-based deep learning models could be explored to improve the accuracy and efficiency of gaze estimation networks. By leveraging self-attention mechanisms and reenforcement learning, future eye-tracking models could dynamically adjust to user behavior, creating a individualised gaze-tracking experience.With these potential research directions, future studies can confer to improving the accurateness, adaptability, and real-world deployment of AI-based
eye-tracking systems, expanding their serviceability in approachability applications, cognitive enquiry, and human-computer interaction.

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