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LULU FILTERIZED LIN'S CORRELATIVE THEIL–SEN REGRESSION-BASED FULLY CONNECTED DEEP MULTILAYER PERCEPTIVE NEURAL NETWORK FOR EYE GAZE PATTERN RECOGNITION

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Abstract: Gaze estimation is process finding the point of gaze on observe axis of eye. Gaze tracking schemes are mainly employed in HCI and study of visual scanning samples. Traditional tracking schemes usually need accurate personal calibration procedure to evaluate the particular eye metrics. In order to improve the accurate gaze estimation, Lulu Filterized Lin's Correlative Theil–Sen Regression-based Fully Connected Deep Multilayer Perceptive Neural Network (LFLCTR-FCDMPNN) is designed for accurate gaze pattern identification through lesser time consumption. Fully Connected Deep Multilayer Perceptive NN contains input layer, three hidden layers, output layer. In input layer, number of gaze images is collected. Then using Lulu nonlinear smoothing filtering method is applied in initial hidden layer for removing noise as well as enhancing image quality. In second hidden layer, Polar coordinate system-based eye-gaze point estimation is performed. Finally, the Gaze Pattern matching is carried out in third hidden layer using Lin's Concordance Correlative Theil–Sen regression. The estimated gaze points are organized at gaze plane to identify gaze patterns. Then pattern matching performed by Lin's Concordance Correlation. In this way, the eye gaze patterns are correctly recognized at the output layer. Experimental evaluation is conducted to demonstrate performance analysis of LFLCTR-FCDMPNN technique through different metrics like gaze pattern recognition accuracy, gaze pattern recognition time, and false-positive rate with different number of eye images. Explained result illustrates which LFLCTR-FCDMPNN method improves the accuracy of gaze pattern recognition and decreases the time consumption than the conventional prediction

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methods. Using the Synthes Eyes dataset, it turned out that the FPR of the suggested LFLCTR-FCDMPNN was 63% higher than existing.

Keywords: Gaze estimation, fully connected deep multilayer perceptive neural network, lulu nonlinear smoothing filtering technique, polar coordinate system-based eye-gaze point estimation, Lin’s Concordance correlative Theil–Sen regression.

MSC: 68T05, 92C55, 68U10.

1. INTRODUCTION

Human visual scheme investigates multifaceted views quickly. It offers imperfect intuitive sources to majority prominent subsets of scenes. Gaze estimation method attempt to forecast human gaze below free-viewing situation. Previous work on accurate human eye gaze estimation is yet to be solved efficiently with minimum complexity.

For forecasting gaze variations of pairwise eye patches with similar individual depend on SNNet, Differential Eyes’ Appearances Network (DEANet) was developed in [1]. But, accuracy for gaze estimation was not enhanced. FARE-Net was introduced in [2] to perform the gaze assessment with the consideration of the variation of left as well as right eyes. However, accurate gaze assessment was not achieved with minimum time consumption.

An improved Itracker integrated with bi-LSTM was designed [3] to recognize the subject’s gazes. But, it failed to effectively enhance performance of subject’s gazes’ estimation. For enhancing performance of eye gaze, Fisher kernels from different generative methods were designed [4]. But, identification accuracy of eye gaze was not improved.

A deep gaze forecast technique was introduced [5] depend on object detection as well as image segmentation. However computational complexity was not reduced. 3Dgaze estimation framework was designed in [6] based on visual attributes of both eyes and the head position. But the time complexity analysis of gaze estimation was not measured. A differential convolutional neural network was developed in [7] for gaze estimation between two eye input images of the equal subject. However image preprocessing was not carried out to enhance accuracy of gaze assessment.

For improving accuracy of gaze assessment, Gaze direction estimation method was introduced in [8]. However it failed to increase robustness of model. 3D gaze estimation with an auto-calibration technique was developed in [9] for accurate measurement. But the time complexity of gaze estimation was not performed. Dynamic causal modeling (DCM) technique was introduced in [10] for gaze processing. But the performance of gaze processing was not improved.

Research in several domains, such as marketing, neuroscience, psychology, and human-computer interface, relies heavily on eye gaze estimation. By recording people's gaze, it sheds light on attention, thought processes, and decision-making, paving the way for a better understanding of human behaviour. Gaze estimation is a tool in the field of human-computer interaction that helps in the creation of gaze-aware interfaces. These interfaces let users operate devices and engage with material simply by moving their eyes. Gaze estimate additionally helps with studies of visual perception, social cognition, and emotional reactions in the fields of neuroscience and psychology. Researchers in the field of marketing also use gaze tracking to learn about customers' habits, evaluate the efficacy of ads, and find the sweet spot for product placement and design.

The assessment of eye gaze accurately does, however, provide a number of difficulties. Estimation accuracy is susceptible to changes in occlusions, lighting, head movement, and eye appearance. In real-world settings or when there are big head movements, traditional methods like video-based systems or infrared eye trackers might not be able to acquire accurate gaze positions. There is also the possibility of estimating mistakes due to calibration techniques and individual variations in eye shape. The limits of existing methods have been extensively studied and documented. These methods include geometric models, appearance-based approaches, and machine learning algorithms. Geometric models necessitate precise alignment and depend on presumptions about the shape of the eyes, whereas appearance-based approaches could have trouble dealing with illumination and occlusion variations. The training datasets for machine learning algorithms can be rather big, and there is a risk of overfitting to certain conditions, which can dramatically reduce their generalizability.

Overall, there are a lot of reasons that make correct estimating difficult, even though eye gaze estimation provides useful information about human behaviour and has many uses. Innovative methods that can reliably estimate gaze in a variety of settings are needed to overcome these obstacles and provide more flexible and efficient gaze tracking systems.

Major contributions:

- A novel deep learning-based technique called LFLCTR-FCDMPNN is introduced for accurate eye gaze estimation with the help of preprocessing, gaze point evaluation, as well as pattern matching incorporated into FCDMPNN.
- To minimize time complexity of gaze pattern recognition, LFLCTR-FCDMPNN uses the Lulu nonlinear smoothing filtering technique in initial hidden layer for removing noise artifacts as well as enhancing image quality. In addition, a Polar coordinate system is applied to estimate the different eye gaze points based on radial distance and theta (θ) (angular coordinate). The estimated points are given to the pattern matching to minimize the time consumption.
- To increase the gaze pattern recognition accuracy, Lin's Concordance Correlative Theil–Sen regression is applied to the Fully Connected Deep Multilayer Perceptive Neural Network. The estimated gaze points are organized in gaze plane. Then pattern matching is performed using Lin's Concordance Correlation. The correlation accurately recognizes the human gazes with the help of ground truth patterns at output layer of DNN. This aids to reduce false positive of pattern detection.
- Finally, comprehensive experiments are performed to estimate quantitative study of LFLCTR-FCDMPNN with existing DL methods depend on different performance parameters.

The manuscript is structured as follows: section 2 reviews literature for gaze pattern estimation. The proposed LFLCTR-FCDMPNN is explained in Section 3. Section 4 describes experimental settings through dataset explanation. Section 5 discusses study of experimental outcomes through dissimilar performance parameters and lastly, section 6 summarizes the manuscript.

An improved method for recognising gaze patterns, the Lulu Filterized Lin's Correlative Theil–Sen Regression–based Fully Connected Deep Multilayer Perceptive

Neural Network (LFLCTR–FCDMPNN), was created and shown as a result of this research. By enhancing the precision and effectiveness of gaze tracking devices, this novel method fills a need in the arena. The LFLCTR-FCDMPNN outperforms conventional approaches by combining methods like Lin's Concordance Correlative Theil-Sen regression, Arctic coordinate system-based eye-gaze point estimation, and Lulu nonlinear smoothing filtering. Improved and more dependable gaze pattern recognition in fields like visual scanning studies and human-computer interaction is one outcome of this study's contribution to the state of the art in eye-tracking technology. An improved method that reduces processing time without sacrificing accuracy is additionally presented.

2. LITERATURE REVIEW

Saliency-based gaze correction (SalientGaze) was performed in [11] for providing the results with better accuracy. However, the performance time complexity analysis remained unaddressed. 3D gaze estimation technique was introduced in [12] using a multi-camera-multilight-source system. However, the calibration error in each step of the gaze estimation process was not reduced. Deep CNN and transfer learning were developed [13] for eye gaze tracking. But, it failed to perform accurate gaze point estimation with minimum complexity.

DCNN was introduced [14] for 3D eye gaze tracking by extracting the iris and pupil pixels of each eye from input images automatically. However, the accuracy of eye gaze tracking was not improved. Geometric transformation models were developed in [15] to redesign eye feature allocation. However, Deep Learning Models (DLP) were not applied to estimate eye-spooring through gaze-mapping calibration.

Gaze point mapping was designed [16] depend on detection of fiducial markers. But precise Gaze point mapping was not achieved. An iris feature-based method was introduced in [17] for 3D gaze estimation. But it failed to reduce the error and increase the accuracy of gaze estimation. A knowledge-based method was introduced in [18] for gaze estimation with low-resolution conditions. However, it failed to enhance the performance of gaze estimation with low-resolution images.

A new technique was introduced in [19] to eliminate the precise user calibration and attain 3-D gaze estimation. However, the designed technique failed to increase the estimation accuracy. Ortho Gaze approach was introduced in [20] that allows the users to operate the 3D position of virtual objects using eye or head gaze alone. However, it failed to perform the discussion regarding the accuracy control of Ortho Gaze, in more complex and practical environments.

A multi layered comparison convolutional neural network (MC-CNN) is employed in the suggested approach to examine the disparities in visual attention between normals and individuals with Alzheimer's Disease (AD). With the use of an eye-tracking system and a 3D comprehensive visual task, MC-CNN is able to collect visual attention heatmaps and achieve a recall of 0.86, precision of 0.82, F1-score of 0.83, and area under the curve (AUC) of 0.90. This allows for the effective diagnosis of AD based on behaviours of eye movement.

When compared to current approaches, the proposed LFLCTR-FCDMPNN Lulu Filterized Lin’s Correlative Theil-Sen Regression-based Fully Connected Deep Multilayer Perceptive Neural Network strives to be more accurate and use less time.

When it comes to noise and poor image quality, traditional gaze tracking techniques could be a pain and frequently necessitate precise personal calibration. But LFLCTR-FCDMPNN takes a different approach by combining various cutting-edge methods to boost performance.

First, to improve the input data reliability, Lulu nonlinear smoothing filtering is used in the initial hidden layer to reduce noise and boost image quality. Accurate gaze estimate relies on this preprocessing phase. Furthermore, by examining the spatial correlations between features, a more robust method for predicting gaze points is achieved by incorporating eye-gaze point estimate based on the Polar coordinate system into the second hidden layer.

In addition, a novel approach to recognising gaze patterns can be achieved by including Lin's Concordance Correlative Theil-Sen regression in the third hidden layer for gaze pattern matching. This method improves recognition accuracy by using statistical correlations to successfully match observed gaze patterns.

In terms of accuracy, false-positive rate, and time consumption, experimental evaluation of LFLCTR-FCDMPNN shows that it outperforms previous approaches. Performance measures compared to traditional prediction methods reveal substantial efficiency and accuracy gains with the suggested approach. In particular, LFLCTR-FCDMPNN outperforms state-of-the-art methods in recognising gaze patterns with reduced processing time, offering a potential solution for practical uses in visual scanning and human-computer interaction research.

In summary, LFLCTR-FCDMPNN is different from other approaches because it uses cutting-edge techniques like Lulu filtering and Lin's regression to improve the efficiency and accuracy of eye gaze pattern detection. Superior testing findings and the fact that it can handle typical problems with gaze tracking highlight how innovative and useful the suggested method is for improving gaze estimation.

A fully connected deep multilayer perceptive neural network based on Lulu Filterized Lin's Correlative Theil-Sen Regression (LFLCTR-FCDMPNN) is suggested as a potential solution to this problem in the study. This innovative method is designed to efficiently detect eye movements and decrease processing time. The network streamlines the gaze pattern recognition process and improves the quality of input data by incorporating techniques such as Lulu nonlinear smoothing filtering, eye-gaze point estimate based on the Polar coordinate system, and Lin's Concordance Correlative Theil-Sen regression. In this regard, LFLCTR-FCDMPNN could be compared to other deep learning approaches such as CNNs for image processing, RNNs for sequential data analysis, and GANs for data augmentation and synthesis. When compared to other gaze pattern recognition systems, these comparisons could provide light on how well LFLCTR-FCDMPNN performs.

By concentrating on improving accuracy and efficiency concurrently, the study fills a particular void in the area of gaze pattern detection. Poor performance from noise in the input data and the need for precise human calibration procedures are common problems with traditional gaze tracking systems. Several improvements are introduced by the proposed LFLCTR-FCDMPNN to fill this gap. In order to improve the input gaze images, it first uses the Lulu nonlinear smoothing filtering approach to reduce noise. Second, it uses eye-gaze point estimate based on the Polar coordinate system to make it more accurate. As a last step, it matches gaze patterns efficiently using Lin's Concordance Correlative Theil-Sen regression. The LFLCTR-FCDMPNN enhances accuracy and reduced processing time compared to standard methods by incorporating these techniques into a fully connected deep multilayer perceptron neural network architecture. There is a big void in the field that this combination of efficiency and accuracy fills, since current methods tend to favour one over the other.

3. PROPOSED METHODOLOGY

Human eye gaze estimation provides significant signs to understand visual attention since the eye movement’s determination is highly-complex [21]. It is wildly required for human-computer interaction, video surveillance, and etc. So, capability to mechanically and correctly track human eye gaze is significant for numerous intelligent schemes. Based on motivation, a novel deep learning technique called LFLCTR-FCDMPNN based eye gaze depth estimation is performed with lesser complexity. A novel LFLCTR-FCDMPNN is developed based on preprocessing, gaze point estimation, as well as pattern matching.

Pre-processing:

Input Layer: Data for the input layer is gaze images.

Lulu Nonlinear Smoothing Filtering: To improve picture quality and eliminate noise, the first hidden layer applies Lulu nonlinear smoothing filtering. To improve gaze photos, Lulu filtering is used because it effectively preserves edge details while smoothing noise.

Gaze Point Evaluation:

Second Hidden Layer: This layer estimates eye-gaze points using the Polar coordinate system. In order to get a better estimate of gaze points, this phase uses a Polar coordinate system to evaluate them. This system takes into account the spatial relationships between features.

Pattern Matching:

Third Hidden Layer: Lin's Concordance Correlative Theil-Sen regression is used to carry out gaze pattern matching in the third hidden layer. To find patterns in gaze data, we use Lin's regression approach, which measures the degree and direction of the link between two variables.

Combination with FCDMPNN (Fully Connected Deep Multilayer Perceptron Neural Network):

Deep multilayer perceptron neural network incorporates the pre-processing, gaze point evaluation, and pattern matching components:

- The output of each pre-processing step is sent into the next layer of the neural network. – Each hidden layer carries out its own computations using the input data and sends the results on to the layer below it.

The last layer of the neural network is responsible for processing the pattern matching results and producing the output that stands in for the identified eye movements.

With the goal to improve the quality of the input data for gaze point evaluation, certain techniques are used. One of them is Lulu nonlinear smoothing filtering, which is selected because it successfully removes noise from gaze images while keeping crucial information.

- The Concordance of Lin Correlative Specifically, the Theil-Sen Regression takes advantage of Lin's regression method's capacity to detect patterns in gaze data and assess correlations across variables. Improvements in pattern matching and gaze pattern recognition are achieved by the use of statistical correlations in Lin's regression.

The LFLCTR-FCDMPNN technique is a strong respond to many problems in visual scanning and human-computer interaction because it uses these preprocessing and analysis methods with a fully linked deep multilayer perceptron neural network to recognise eye gaze patterns efficiently and accurately.

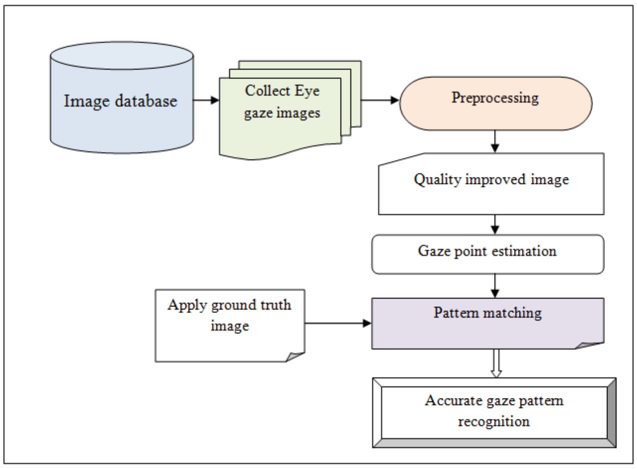

Figure 1: Flow process of proposed LFLCTR-FCDMPNN technique

Figure 1 demonstrates flow process of LFLCTR-FCDMPNN method for gaze pattern estimation. First, the numbers of eye gaze images are gathered as of dataset. In first stage, image preprocessing performed using Lulu nonlinear smoothing filtering technique to reduce complexity of eye gaze pattern categorization. Secondly, gaze point estimation is performed using Polar coordinate system. Finally, the pattern matching is performed using Lin’s Concordance Correlative Theil–Sen regression with the estimated gaze point and the ground truth point.

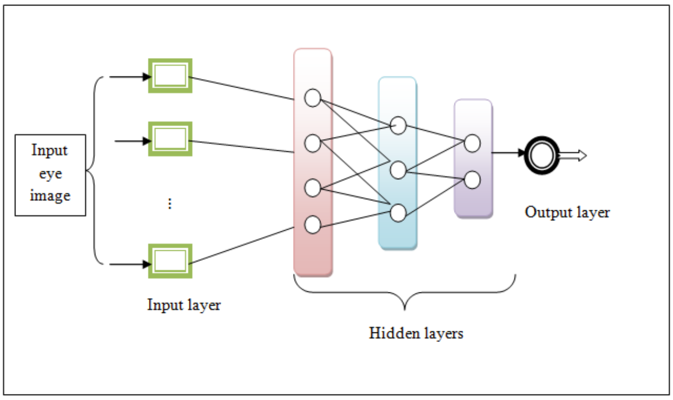

Figure 2: Schematic structure of Fully Connected Deep Multilayer Perceptive Neutral

Figure 2 demonstrates Schematic structures of a deep neural network. The layers comprise neurons as nodes are connected as of one layer to a consecutive layer with adjustable weights. Input layer considers eye gaze images as input. In initial hidden layer, image preprocessing is performed to remove noise artifacts. After that, gaze point estimation process is said to be performed in 2nd hidden layer. Finally, gaze pattern categorization is carried out in third hidden layer. As a result, gaze estimation is obtained at output layer.

A comparison with other top-tier deep learning models for gaze pattern recognition is something the authors might look into doing to improve the methodology. Although the LFLCTR-FCDMPNN is a novel strategy, it would be instructive to compare its results to those of current models to determine its efficacy and superiority. To further improve the model's performance, the authors could think about optimising the architecture and hyperparameters using methods like grid search or Bayesian optimisation.

The model's performance could be optimised across many datasets and circumstances with this adaptive technique, guaranteeing its robustness and generalizability.

In order to confirm that the suggested method is reliable and robust, the authors should think about adding further controls. To test the model's performance in different settings, it may be necessary to use datasets that represent a wide range of demographics, environmental factors, and eye movements. Further assurance in the model's performance could be achieved by utilising sensitivity analysis and cross-validation techniques to evaluate its consistency and stability. Further validation of the model's practical value and reliability could be achieved by testing it in real-world settings with real-time gaze tracking systems.

Lulu nonlinear smoothing filtering-based Preprocessing

Preprocessing is the process of removing the noise and enhancing the image for restoration. Preprocessing of an image is significant aspect of digital image processing. Aim of preprocessing is to enhance image quality before the gaze point estimation. The proposed LFLCTR-FCDMPNN technique uses the Lulu nonlinear smoothing filter for enhancing the image quality. Lulu nonlinear smoothing filter is a nonlinear mathematical technique for removing noise from a by taking a moving average.

Let us assume image dataset 'D' through number of eye gaze images '$I_1, I_2, I_3, \dots . I_n$' '$n$' represents whole number of images. Number of pixels in every image is represented by $v_1, v_2, v_3, \dots . v_m$. Then the image pixels are organized in kernel filtering window in rows as well as columns.

v_1	v_2	v_3	v_4	v_5
v_6	v_7	v_8	v_9	v_{10}
v_{11}	v_{12}	v_{ij}	v_{14}	v_{15}
v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
v_{21}	v_{22}	v_{23}	v_{24}	v_{25}

Figure 3: 5*5 kernel filtering window

Figure 3 depicts $5 * 5$ kernel filtering window. Then pixels are sorted into ascending order and take middle pixel value. If some two pixels are in center pixel, after that average of these pixels is taken as center. Lulu nonlinear smoothing filter is worked based on two operators L and U which represent the 'lower' and 'upper. It means that the neighboring pixels are selected below or above the upper of the center pixel (v_{ij}). The neighboring pixels are segmented as given below,

$$v_n = \left[v_{(i-1,j)}, v_{(i+1,j)}, v_{(i,j-1)}, v_{(i,j+1)}\right] \tag{1}$$

Were, v_n denotes a neighboring pixel of the center pixels 'v_{ij} '. From the above equation (1), there are four neighboring pixels are selected from above or below the center value. The noise filtered output as given below,

$$F = \mu + \left\|v_{ij} - \mu\right\| \tag{2}$$

Where F represents the filtered output, μ denotes a local mean of neighboring pixels inside filtering window, 'v_{ij}' denotes a center pixels.

Polar coordinate system-based eye-gaze point evaluation

Following the image preprocessing, eye gaze points are evaluated by a Polar coordinate scheme. In mathematics, polar coordinate scheme is 2D coordinate scheme at that every point on plane is calculated through distance as of reference point as well as angle from reference direction. Angle is named angular coordinate as well as angles in polar notation are normally denoted in degree.

Figure 4 illustrates polar coordinate scheme in 2D space to estimate the set of boundary points used to form a gaze pattern. By applying the polar coordinate system, the points are marked to estimate gaze patterns. This helps to reduce the time consumption of gaze pattern classification.

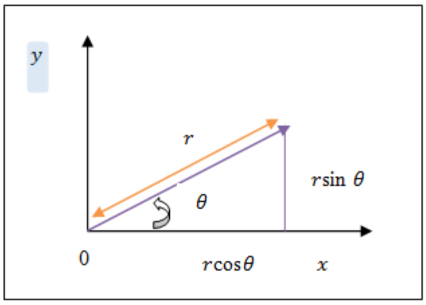

Figure 4: Polar coordinate system

Figure 5 illustrates the gaze point's estimation using a polar coordinate system. Polar coordinates 'r' (radial distance), theta (θ) are defined in terms of polar coordinate is calculated by applying the Pythagoras theorem,

$$r = \sqrt{x^2 + y^2} \tag{3}$$

$$\theta = \frac{\mathrm{r} \sin\theta \, y}{r \cos\theta \, y} = \tan\theta \left(\frac{y}{x}\right) \tag{4}$$

$$\theta = \tan^{-1}\left(\frac{y}{x}\right) \tag{5}$$

By using (3), (4), (5), the radial distance and angular coordinates are measured and the gaze points are estimated. Likewise, all points are noted in gaze plane. As outcome, dissimilar points are attained depend on motion of eyelid. This aids to identify gaze patterns through lesser time.

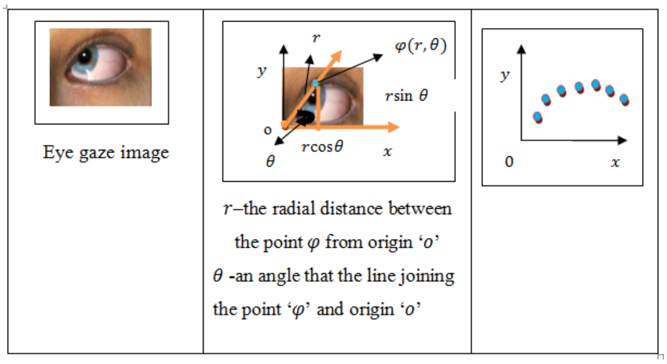

Figure 5: Gaze Point's Estimation using a polar coordinate system

Lin's Concordance Correlative Theil–Sen regression-based pattern classification

The obtained gaze points are organized in gaze plane to identify gaze patterns. Gaze pattern detection is performed in third hidden layer of DL by means of Lin's Concordance Correlative Theil–Sen regression. Theil–Sen regression is ML method for robustly examining the two sample points in the plane by finding Lin's Concordance Correlation function. The regression function uses correlation between the gaze points and ground truth patterns.

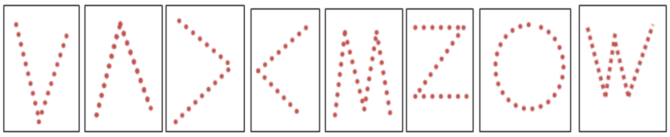

Figure 6: Ground-truth gaze patterns

Figure 6 demonstrates the ground truth patterns. Evaluated gaze patterns through ground truth patterns are coordinated depend on Lin's Concordance Correlation.

$$\rho = \frac{2 * v_{pes} v_{pgt}}{v_{pes^2} + v_{pgt^2} + \left(p_{es} - p_{gt}\right)^2} \tag{6}$$

Where, $v_{p_{es}}$ denotes a variance of estimated gaze patterns, $v_{p_{gt}}$ indicates a variance of ground truth gaze patterns, p_{es} indicates an estimated gaze pattern, p_{gt} indicates ground-truth gaze patterns. Lin's Concordance Correlation coefficient gives outcomes from 0 to 1:

$$\rho = \begin{cases} +1, & \text{patterns are correctly matched} \\ 0, & \text{patterns are not correctly matched} \end{cases} \tag{7}$$

Lin's Concordance Correlative coefficient provides the results '1' when the patterns are correctly matched. Otherwise, the correlative coefficient returns '0'. In this way, accurate pattern matching is performed at the output layer. The LFLCTR-FCDMPNN algorithmic process is described as given below.

// Algorithm 1: Lulu Filterized Lin's Correlative Theil–Sen Regression-based Fully Connected Deep Multilayer Perceptive Neural Network

Input: Dataset, Number of eye gaze images '$I_1, I_2, I_3, \ldots. I_n$,

Output: Increase the accuracy

Begin

Step 1: **Collect the number of** eye gaze images '$I_1, I_2, I_3, \ldots. I_n$ taken as input at the input layer
Step 2: **Foreach** eye gaze image // **hidden layer 1**
Step 3: Apply Lulu nonlinear smoothing filtering technique
Step 4 Extract the number of pixels $v_1, v_2, v_3, \ldots v_m$
Step 5: Arrange the pixels in the filtering window
Step 8: Take center pixel value 'v_{ij}'
Step 9: Find pixels that deviate from the center pixel
Step 10: Remove the noisy pixels
Step 11: **return** (quality-improved eye gaze image)
Step 12: **For each** preprocessed image // **hidden layer 2**
Step 13: Apply polar coordinate system using (3) (4) (5)
Step 14: Obtain the gaze points
Step 15: **End for**
Step 16: Obtained gaze points are arranged in gaze plane // **hidden layer 3**
Step 17: **For each estimated gaze pattern and ground truth patterns**
Step 18: **Measure correlation** 'ρ'
Step 19: **if** ($\rho = 1$) **then**
Step 20: Patterns are correctly matched
Step 21: **else**
Step 22: Patterns are not matched
Step 23: **End if**
Step 24: **End for**
End

Algorithm 1 describes the process of gaze patterns recognition with higher accuracy. The FCDMPNN includes multiple layers to study given input eye gaze images. Input layer obtain number of eye gaze images. In initial hidden layer, Lulu nonlinear smoothing filtering method is applied for enhancing image quality through eliminating noise. Afterward, polar coordinate system is used to second hidden layer of DNN for estimating the gaze points. Lastly, gaze patterns are coordinated through ground truth patterns using Lin's Concordance Correlative Theil–Sen regression in third hidden layer. Finally, accurate recognition is attained at output layer.

4. EXPERIMENTAL ASSESSMENT

In this section, experimental evaluation of LFLCTR-FCDMPNN and conventional DEANet [1] FARE-Net [2] is executed by MATLAB through two dissimilar eye image datasets such as synthes Eyes and MPII gaze. Synthes Eyes dataset (https://www.cl.cam.ac.uk/research/rainbow/projects/syntheseyes/) contain 11,382 synthesized close-up images of eyes. Other dataset is the MPII gaze dataset that is considred from https://www.kaggle.com/chethanhebbar/mpii-modified-dataset. This dataset includes 213,659 images taken as of 15 different contestant s through natural daily laptop employ in excess of three months. It has a huge changeability in appearance and illumination.

5. RESULTS

Results of LFLCTR-FCDMPNN and existing DEANet [1], FARE-Net [2] are obviously explained in this part. Different parameters are employed for measuring performance of three dissimilar techniques. Performance study is performed by a table and graphical representation.

GPRA: It measured as number of gaze patterns of eye images are identified from whole number of ye gaze images. The accuracy is formulated as given below,

$$\boldsymbol{GPRA} = \left(\frac{\boldsymbol{no.of\ gazepatterns\ of\ eyeimagesare\ recognized}}{\boldsymbol{n}} * \mathbf{100}\right) \tag{8}$$

Where $GPRA$ denotes Gaze pattern recognition accuracy, 'n' indicates number of eye images and it calculated in percentage (%).

False-positive **rate**: It is calculated as number of gaze patterns of eye images that are incorrectly recognized. It is expressed as below,

$$\boldsymbol{FPR} = \left(\frac{\boldsymbol{no.of\ gazepatterns\ of\ eyeimagesare\ incorrectly\ recognized}}{\boldsymbol{n}} * \mathbf{100}\right) \tag{9}$$

Where, FPRdenotes false-positive rate and it is calculated in percentage (%).

Time complexity: It is measured as amount of time taken through algorithm to identify gaze patterns with number of eye gaze images. Overall time consumption measured as follows

$$\boldsymbol{TC} = [\boldsymbol{n}] * \boldsymbol{T}(\boldsymbol{gazepatternrecognition}) \tag{10}$$

From (12), TC represents time complexity, T indicates time for recognizing the gaze patterns.

Tables 1(a) and 1(b) show the Gaze pattern recognition accuracy using synthesEyes dataset and MPII gaze of the proposed LFLCTR-FCDMPNN. Tabulated results confirm Gaze pattern recognition accuracy using LFLCTR-FCDMPNN upon comparison with the other two existing methods [1] and [2]. Let us assume number of gaze images 1000 considered from synthesEyes dataset. Therefore, accuracy of the proposed LFLCTR-FCDMPNNis 94% and the existing DEANet [1], FARE-Net [2] are 89%, 87%. Afterward which, the nine different outcomes are examined along with the various input gaze images. Finally, the performance of LFLCTR-FCDMPNN is compared to conventional techniques. Overall comparison result noticed which recognition accuracy by LFLCTR-FCDMPNN is increased by 7% and 10% than the DEANet, FARE-Net.

Table 1(a): Gaze pattern recognition accuracy

Number of eye gaze images	**Gaze pattern recognition accuracy using Synthes Eyes**		
	LFLCTR-FCDMPNN	**DEANet**	**FARE-Net**
1000	94	89	87
2000	94.5	87.5	87.5
3000	95.06	88.33	85.33
4000	93.75	89	85.5
5000	95	87.6	85
6000	95.83	90.33	88.66
7000	94.07	89.71	87.85
8000	95.65	88.12	86.87
9000	95.22	89.11	86.11
10000	96.45	88.5	87.25

Table 1(b): Gaze pattern recognition accuracy

Number of eye gaze images	Gaze pattern recognition accuracy using SynthesEyes		
	LFLCTR-FCDMPNN	DEANet	FARE-Net
1000	92	87.5	86.5
2000	92.5	87	85
3000	94.66	87.66	85.16
4000	93.25	88.62	85
5000	94.8	87	84.2
6000	94.16	89.41	87.75
7000	93.5	88.35	86.92
8000	95.37	87.87	85.68
9000	95.05	89	86.05
10000	95.85	88.1	86.5

Let us consider the 10000 from the MPII gaze dataset. Gaze pattern recognition accuracy of LFLCTR-FCDMPNN is 92% and the accuracy of DEANet [1], FARE-Net [2] are 87.5% and 86.5%. Likewise, the accuracy of different results is obtained. Performance of LFLCTR-FCDMPNN is compared to the results of DEANet [1], FARE-Net [2]. The overall results indicate that the recognition accuracy of LFLCTR-FCDMPNN is enhanced by 7% and 10% than the existing methods.

Figures 7(a) and 7(b) demonstrate the accuracy with respect to gaze images collected from the dataset. From observed results, accuracy was found to be improved using the proposed LFLCTR-FCDMPNN when compared to ofDEANet [1], FARE-Net [2]. This is due to the application of Lin's Concordance Correlative Theil–Sen regression into the Fully Connected Deep Multilayer Perceptive Neural Network. In the third hidden layer, Lin's Concordance Correlation is used to estimate the gaze patterns and ground truth patterns.

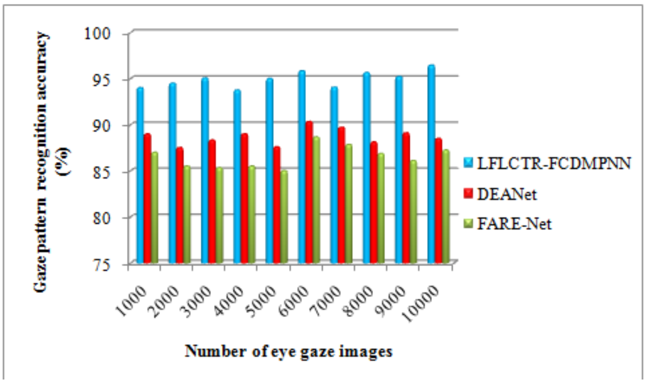

Figure 7(a): Gaze Pattern Recognition accuracy Syntheseyes dataset

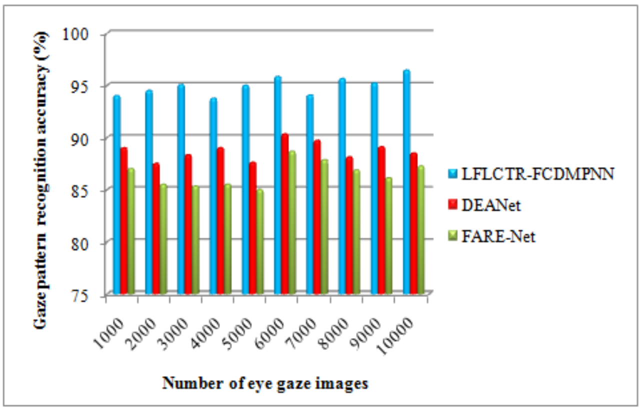

Figure 7(b): Gaze Pattern Recognition accuracy using MPII gaze dataset

Based on the Correlation measure, the eye gaze patterns are correctly recognized.

Tables 2(a) and 2(b) illustrate the experimental outcomes of FPRusing LFLCTR-FCDMPNN, DEANet [1], FARE-Net [2] with number of eye gaze images. Obtained result verifies which FPR is considerably reduced by LFLCTR-FCDMPNN than the existing two conventional methods. Through using synthes Eyes dataset, $FPR$of proposed LFLCTR-FCDMPNN was found to be increased by 55% and 63% when compared to DEANet [1], FARE-Net [2]. Let us consider the MPII gaze dataset, false-positive rate of the proposed LFLCTR-FCDMPNNwas found to be increased by 51% and 58% when compared to DEANet [1], FARE-Net [2] respectively.

Table 2(a): False-Positive rate

Number of eye gaze images	**False- Positive rate (%) using SynthesEyes**		
	LFLCTR-FCDMPNN	**DEANet**	**FARE-Net**
1000	6	11	13
2000	5.5	12.5	14.5
3000	4.93	11.66	14.66
4000	6.25	11	14.5
5000	5	12.4	15
6000	4.16	9.66	11.33
7000	5.92	10.28	12.14
8000	4.35	11.87	13.12
9000	4.77	10.88	13.88
10000	3.55	11.5	12.75

Table 2(b): False- Positive rate

Number of eye gaze images	False- Positive rate (%) using MPII gaze		
	LFLCTR-FCDMPNN	DEANet	FARE-Net
1000	8	12.5	13.5
2000	7.5	13	15
3000	5.33	12.33	14.83
4000	6.75	11.37	15
5000	5.2	13	15.8
6000	5.83	10.58	12.25
7000	6.5	11.64	13.07
8000	4.62	12.12	14.31
9000	4.94	11	13.94
10000	4.15	11.9	13.5

Figures 8(a) and 8(b) demonstrate the false positive rate of LFLCTR-FCDMPNN, DEANet [1], FARE-Net [2]. The figure inferred that the LFLCTR-FCDMPNN technique relatively reduces $FPR$when compared to conventional methods. This is due to application of Lin's Concordance Correlative Theil–Sen regression. The Theil–Sen regression is applied for measuring the correlation between evaluated gaze as well as ground truth gaze patterns by Lin's Concordance correlation. Where the patterns are correctly matched, the correlation coefficient returns'1'. Otherwise, the correlation coefficient returns'0'. This helps to minimize incorrect pattern recognition and increase the accuracy at the output layer.

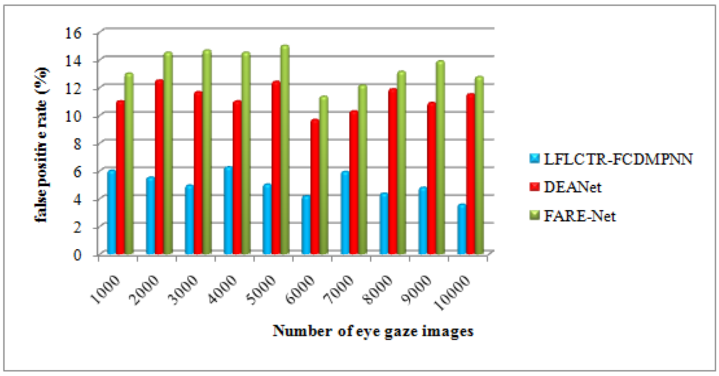

Figure 8(a): Gaze Pattern Recognition accuracy using Syntheseyes dataset

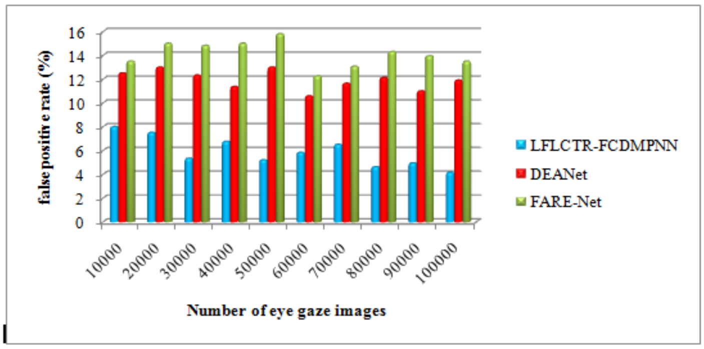

Figure 8(b): Gaze Pattern Recognition Accuracy using MPII gaze dataset

The time complexity using three methods namely LFLCTR-FCDMPNN, DEANet [1], FARE-Net [2] are reported in tables 3(a) and 3(b) using synthes Eyes dataset and MPII gaze dataset. In table 5, the time complexity for three different techniques obtain enhanced as enhancing number of gaze images. Amongst three techniques, LFLCTR-FCDMPNN better well in attaining lesser TC. Through '1000' gaze images are gathered as of synthes Eyes dataset for experimentation, time complexity was found to be '$55ms$' using the LFLCTR-FCDMPNN technique, '58ms' are observed using [1], and $62ms$' when applied [2]. For every technique, ten different outcomes are attained through dissimilar counts of input gaze images. Therefore, overall TC of LFLCTR-FCDMPNN method is compared to conventional methods. Average of ten comparison outcomes shows which TC of LFLCTR-FCDMPNN is considerably minimized by 7% and 14% than the [1],[2]. Similarly, by applying MPII gaze dataset, overall TC of LFLCTR-FCDMPNN is lesser by the means of 7% and 14% when compared to DEANet [1], FARE-Net [2] respectively.

Table 3(a): Time Complexity

Number of eye gaze images	**Time Complexity (ms) using SynthesEyes**		
	LFLCTR-FCDMPNN	**DEANet**	**FARE-Net**
1000	55	58	62
2000	60	64	68
3000	63	66	72
4000	68	72	76
5000	70	75	80
6000	72	78	84
7000	77	84	91
8000	81.6	85.6	96
9000	83.7	87.3	99
10000	91	95	100

Table 3(b): Time Complexity

Number of eye gaze images	Time Complexity (ms) using MPII gaze		
	LFLCTR-FCDMPNN	DEANet	FARE-Net
1000	72	78	81
2000	80	90	96
3000	84	93	105
4000	88	96	104
5000	90	97	107.5
6000	96	102	108
7000	98	105	112
8000	104	112	120
9000	112.5	117	126
10000	118	125	130

Figures 9(a) and 9(b) demonstrate performance of TC of gaze pattern recognition using three methods LFLCTR-FCDMPNN, DEANet [1], FARE-Net [2]. Therefore, TC was examined in graph is comparative to number of gaze images. Enhancing number of gaze images, improve in TC also. Amongst three techniques, LFLCTR-FCDMPNN technique minimizes the complexity of gaze pattern recognition. This is owing to application of image preprocessing, and gaze point estimation. In image preprocessing, Lulu nonlinear smoothing filtering technique is applied in initial hidden layer for removing noise as well as enhancing image quality. In addition, the Polar coordinate system is applied to evaluate eye gaze points. With the estimated gaze points, the classification is carried out to reduce TC of pattern recognition and decrease the time consumption.

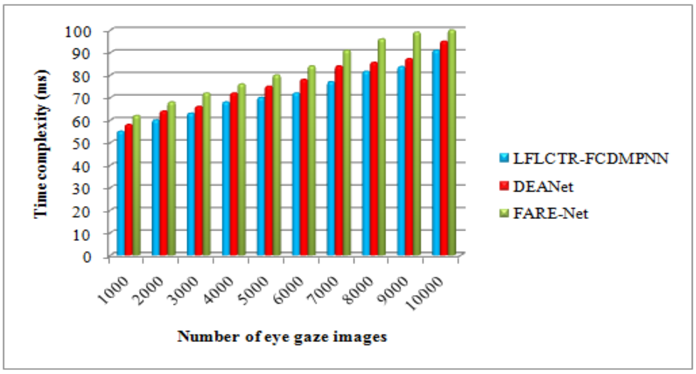

Figure 9(a): Time complexity using synthes Eyesdataset

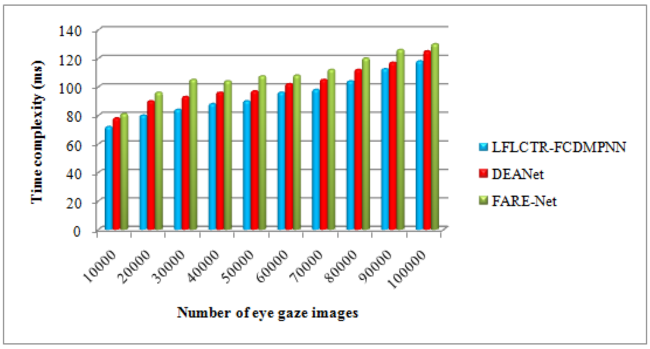

Figure 9(b): Time complexity using MPII gaze dataset

Evaluate the performance of the model numerically as part of quantitative analysis of the experimental results. In general, the fraction of correct forecasts is what we call accuracy. The precision of a model is defined as its capacity to prevent false positives, which is measured by the ratio of true positives to all positive predictions. Model accuracy in detecting all relevant instances is measured by recall, which is defined as the ratio of true positives to all actual positives. To provide a more equitable evaluation, F1-score combines recall and precision into a single statistic. Qualitative analysis goes farther into comprehending how the model acts. It comprises improving interpretability, looking at misclassifications, and determining important traits. To validate model predictions and guide improvements, it is helpful to include domain knowledge into qualitative analysis.

6. CONCLUSION

A new DL-based gaze estimation technique called LFLCTR-FCDMPNN is introduced to improve gaze estimation performance. First, image preprocessing is employed through using Lulu nonlinear smoothing filtering method in initial hidden layer for removing noise as well as enhancing image quality. Followed by, a Polar coordinate system is applied to estimate the eye gazepoints. These gaze points are arranged at the gaze plan. Finally, Gaze Pattern recognition is performed using Lin's Concordance Correlative Theil–Sen regression. The estimated gaze points are organized in gaze plane to identify gaze patterns by using Lin's Concordance Correlation. Experimental results demonstrate performance of LFLCTR-FCDMPNN compared to different conventional methods. Also, comparison outcomes denote which the LFLCTR-FCDMPNN better in prediction accuracy, FPR, prediction time. Also, it is shown that the HDMPJCR-DMPFFN increases $GPRA$ and reduces time and FPRthan the conventional approaches.

Even if the method that has been suggested has some promise, it is vital to recognise the limitations of the method and to identify potential possibilities for further research. When applied to bigger datasets or real-world applications, it may run out of steam due to insufficient processing power or resources. There may be a need for additional generalisation and adaptation if the technique's efficacy varies across different types of data or domains. Approaches to improve scalability, generalizability to varied datasets, and model interpretability could be investigated in future research using approaches like explainable artificial intelligence. Researching how well the method handles different types of data noise and uncertainty could also provide useful information. Resolving these constraints will allow the suggested method to be applied more effectively and with more flexibility in real-world contexts.

The study's findings are in accordance with the arguments and evidence offered throughout. Highlighting its novel approach to improving accuracy and efficiency, the research outlines the development and implementation of the Lulu Filterized Lin's Correlative Theil–Sen Regression–based Fully Connected Deep Multilayer Perceptive Neural Network (LFLCTR-FCDMPNN) for gaze pattern recognition. Lulu nonlinear smoothing filtering, eye-gaze point estimation based on the Polar coordinate system, and Lin's Concordance Correlative Theil-Sen regression are only a few of the methods described in depth in the paper.

Using the Synthes Eyes dataset, it turned out that the FPRof the suggested LFLCTR-FCDMPNN was 63% higher than existing.

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