A Hybrid GAN-BiGRU Model Enhanced by African Buffalo Optimization for Diabetic Retinopathy Detection

Dr. Sasikala P[1], Sushil Dohare[2], Dr. Mohammed Saleh Al Ansari[3], Janjhyam Venkata Naga Ramesh[4], Prof. Ts. Dr. Yousef A.Baker El-Ebiary[5], Dr. E.Thenmozhi[6]

Assistant professor, Department of Computer Science,
Government Science college (Nrupathunga University), Bangalore, Karnataka[1]
Department of Epidemiology, College of Public Health and Tropical Medicine, Jazan University, Saudi Arabia[2]
Associate Professor, College of Engineering, Department of Chemical Engineering, University of Bahrain, Bahrain[3]
Assistant Professor, Department of Computer Science and Engineering,
Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India[4]
Faculty of Informatics and Computing, UniSZA University, Malaysia[5]
Associate Professor, Department of Information Technology, Panimalar Engineering College, Chennai, India[6]

***Abstract*—Diabetic retinopathy (DR) is a severe complication of diabetes mellitus, leading to vision impairment or even blindness if not diagnosed and treated early. A manual inspection of the patient's retina is the conventional way for diagnosing diabetic retinopathy. This study offers a novel method for the identification of diabetic retinopathy in medical diagnosis. Using a hybrid Generative Adversarial Network (GAN) and Bidirectional Gated Recurrent Unit (BiGRU) model, further refined using the African Buffalo Optimization algorithm, the model's capacity to identify minute patterns suggestive of diabetic retinopathy is improved by the GAN's skill in extracting complex characteristics from retinal pictures. The technique of feature extraction plays a critical role in revealing information that may be hidden yet is essential for a precise diagnosis. Then, the BiGRU part works on the characteristics that have been extracted, efficiently maintaining temporal relationships, and enabling thorough information absorption. The combination of GAN's feature extraction capabilities with BiGRU's sequential information processing capability creates a synergistic interaction that gives the model a comprehensive grasp of retinal pictures. Moreover, the African Buffalo Optimization technique is utilized to optimize the model's performance for improved accuracy in the identification of diabetic retinopathy by fine-tuning its parameters. The current study, which uses Python, obtains a 98.5% accuracy rate and demonstrates its amazing ability to reach high levels of accuracy in Diabetic Retinopathy Detection.**

Keywords*—*African Buffalo Optimization (ABO); Bidirectional Gated Recurrent Unit (BI-GRU); Generative Adversarial Network (GAN); diabetic retinopathy; medical diagnosis

I. INTRODUCTION

Diabetic retinopathy is a significant and escalating public health concern that affects individuals with diabetes, representing a leading cause of blindness worldwide [1] .This progressive eye disease is primarily attributed to prolonged exposure to elevated blood sugar which can lead to impairment of the blood vessels in the retina, the light-sensitive tissue at the back of the eye. These blood vessels may start to leak blood or other fluids into the eye as they degrade, which can cause retinal edema, blurred vision, and eventually vision loss [2]. Regular screening and early identification are essential for successful intervention and management of diabetic retinopathy since the severity of the condition might vary, and its development may be asymptomatic in its early stages. Overall, ophthalmologists' dilated eye exams have been the gold standard for detecting diabetic retinopathy [3]. While these tests are still necessary, the rising incidence of diabetes and the danger of diabetic retinopathy that goes along with it highlight the need for effective and scalable diagnostic measures [4]. Medical imaging and artificial intelligence (AI) have made amazing strides in recent years, and these developments are increasingly being used to transform the identification of diabetic retinopathy [5]. There are many phases of diabetic retinopathy, from non-proliferative retinopathy, which is milder, to proliferative retinopathy, which is more severe and involves the development of aberrant blood vessels on the retina. Early identification is important because it allows for appropriate management to stop or postpone vision loss, preserving patients' visual function and general quality of life. Diagnosing diabetic retinopathy has mostly included dilated eye exams performed by qualified ophthalmologists. In these tests, dilating eye drops are used to provide a thorough view of the retina, which is followed by a careful visual assessment [6]. Despite being extremely precise, this procedure is time- and resource-consuming, and human interpretation might vary. It also presents a major accessibility and scalability barrier, particularly in areas with poor access to eye care professionals. The development of non-invasive, high-resolution imaging methods for the retina is the result of developments in medical imaging [7] They provide precise observation of retinal structures and abnormalities, such as Ophthalmic coherence tomography, and fundus photography (OCT), and fluorescein angiograph. Although these methods of imaging have increased diagnostic precision and allowed

for early diagnosis, they continue to depend on human judgment and are prone to differences in skill

Huge collections of retinal pictures are being used to models so they can identify the telltale symptoms of diabetic retinopathy [8]. These DL-driven solutions have shown outstanding diagnostic speed, accuracy, and consistency; they also possess the potential to supplement current approaches and reduce access to care gaps [9]. The conditions of detecting diabetic retinopathy may change as a result of the combination of DL and medical imaging [10]. Automation of image processing has the potential of expanding screening accessibility, easing the strain on healthcare resources, and enhancing diagnosis precision, particularly in areas where access to ophthalmologists is constrained [11]. The ramifications of these developments, particularly their effect on patient outcomes and healthcare delivery, will be explored in this study. With an emphasis on how this convergence might help preserve sight and improve the quality of life for people with diabetes, researchers will also examine existing research, difficulties, and the future potential of DL in diabetic retinopathy diagnosis. The main issue with diabetic retinopathy is that it progresses initially without any symptoms. Early identification is crucial because patients may not become aware of the disease until it has progressed to an advanced stage. From moderate non-proliferative retinopathy to severe proliferative retinopathy, the disorder progresses through numerous phases and is defined by the growth of aberrant blood vessels in the retina [12]. Effective management can stop or delay vision loss, preserving the quality of life for those with diabetes, therefore early detection of diabetic retinopathy is essential (Lin et al. 2021). While conventional diagnostic methods are dependable, they can also be resource-intensive and not always accessible, particularly in places where there are few or no access to eye care practitioners. As a result, investigating cutting-edge methods like artificial intelligence and enhanced medical imaging has become a potential direction to solve this important healthcare issue [13].Technology is becoming increasingly important in the transformation of diabetic retinopathy diagnosis. [14]. In order to provide facts about the history, current, and destiny of this crucial field of healthcare, this investigation aims to shed light on the changing landscape of diabetic retinopathy detection.An innovative method that combines the benefits of Generative Adversarial Network (GAN) with Bidirectional Gated Recurrent Units (BiGRUs) for improved image processing is called the African Buffalo Optimization Guided Hybrid GAN-BiGRU. GAN are excellent at handling spatial data, but BiGRUs are good at handling sequential data. This study presents a possible structure for a wide range of applications, promising enhanced accuracy and efficiency in image analysis and pattern identification by combining these two deep learning paradigms and the African Buffalo Optimization method.

The proposed research aims to address these limitations by introducing "A Hybrid GAN-BiGRU Model Enhanced by African Buffalo Optimization for Diabetic Retinopathy Detection." The significance of this research lies in its potential to provide a more efficient, accessible, and accurate method for the early detection and diagnosis of diabetic retinopathy. The gap in existing knowledge that the study aims to fill is the development of a novel approach that combines advanced neural network architectures (GAN and BiGRU) with a bio-inspired optimization technique (African Buffalo Optimization) to enhance the precision and efficiency of diabetic retinopathy detection.

The following are the study's key contributions.

- Proposes a hybrid Generative Adversarial Network (GAN) and Bi-directional Gated Recurrent Unit (BiGRU) model for diabetic retinopathy detection.
- Implements the African Buffalo Optimization algorithm to refine and optimize the model's performance, enhancing its efficiency.
- Enhances the identification of subtle patterns associated with diabetic retinopathy by leveraging GAN's effective feature extraction capabilities from retinal images.
- Highlights the crucial role of feature extraction in revealing hidden information essential for precise diagnoses in diabetic retinopathy.
- Demonstrates the contribution of Bi-directional Gated Recurrent Unit (BiGRU) in maintaining temporal relationships and facilitating thorough information absorption from the extracted characteristics.
- Explores the synergistic interaction between GAN's feature extraction and BiGRU's sequential

Overall, the study contributes to advancing the field of diabetic retinopathy diagnosis by combining advanced neural network architectures and bio-inspired optimization techniques for precise and efficient detection. The format for the enduring paragraphs is as follows: The relevant work based on various methodologies for diabetes prediction is examined in Section II, and the research gap is identified in section III. The feature selection and classification process for the proposed method is explained in the Section IV. The outcomes and considerations are covered in Section V; the prospective applications for the future are covered in Section VI.

II. Related Works

The disease known as diabetic retinopathy (DR), which obliterates the retinal veins, can cause blind. To diagnose this lethal illness, colored fundus injections are frequently used. The manual examination of the aforementioned photos (by physicians) is tedious and prone to mistakes. As a result, a variety of computer vision engineering approaches are used to forecast the DR's appearances and phases autonomously.

These techniques can't properly categorize DR's various phases since they are operationally costly and don't retrieve extremely nonlinear information. In order to hasten the training of models and convergence, Khan et al. [15] focuses on categorizing the DR's several phases by means of the minimum constraints that may be learned feasibleThe VGG-NiN paradigm is built by stacking the VGG16, the spatial pyramid layer for pooling (SPP), and the network-in-network (NiN). It is a highly nonlinear scale-invariant deeper method. The recommended VGG-NiN device is capable of handling a DR image of any dimension in along with the benefits of the SPP layer. The framework also gains extra nonlinearity from the stacking of NiN, which enhances classification overall. The recommended strategy beats cutting-edge approaches when it comes to of efficiency and effective use of computer resources, according to data from experiments. The model's construction and preprocessing techniques need to be changed to boost output.

Identifying diabetic retinal disease in its early stages and predicting the potential presence of Micro aneurysms in fundus images were incredibly challenging for a long time. Long-term high blood glucose levels cause diabetic retinopathy (DR), which. The field of deep learning is quickly advancing, results in micro vascular problems and permanent blindness. The initial indications of DR are the development of micro aneurysms and macular edema in the retina, and prompt detection can decrease the chance of developing non-proliferated diabetic retinopathymaking it an effective method for offering an intriguing answer to difficulties involving clinical picture interpretation. (Qiao, Zhu, and Zhou [16] proposed system analyzes the existence of a micro aneurysm in a fundus image via convolutional neural network techniques that incorporate a deep learning approach as an essential element and are accelerated by a GPU (Graphics Processing Unit). This will enable outstanding performance and low-latency inference for the identification and segmentation of medical images. The fundus image is categorized as normal or diseased using the semantic segmentation technique The process of semantic segmentation divides the image pixel into groups based on their common semantics in order to identify a micro aneurysm's characteristics. This gives ophthalmologists a computerized method to help them classify fundus pictures as quickly, mild, or extreme NPDR. The early identification and prognosis method for non-proliferative diabetic retinopathy was suggested, and it has the ability of successfully developing a deep convolution neural network (CNN) for semantic division of retina images, which can improve the efficacy and precision of NPDR (non-proliferated diabetic retinopathy) prediction. It is essential to conduct testing on various datasets and in real-life healthcare environments to determine the system's usefulness and dependability.

Among the conditions that poses the greatest risk to vision is retinopathy caused by diabetes (DR), a consequence brought on by elevated blood sugar levels. However, an ophthalmologist must manually collect DR screening, which is time-consuming and subject to error. The enormous rise in the number of diabetic patients has led to an emphasis on automated DR diagnosis in recent years. Additionally, Convolutional Neural Networks (CNN) have proven themselves to be state-of-the-art for DR stage diagnosis in recent times. (Farag, Fouad, and Abdel-Hamid [17]offers a fresh, a system that autonomously learns how to calculate brightness from just one Colour Fundus Photograph (CFP). The suggested method builds a visual embedding using DenseNet169's encoder. Convolutional Block Attention Module (CBAM) is also added on the highest of the encoder to boost its ability to discriminate. The algorithm is then trained using the Kaggle Asia Pacific Tele-Ophthalmology Society (APTOS) database utilizing cross-entropy loss. .THIS approach makes a substantial contribution by accurately classifying the degree of diabetic retinopathy intensity while requiring less time and spatial difficulty, making it a potential contender for autonomous diagnosis. the effectiveness of various CBAM designs. It is recommended to apply several unbalanced learning algorithms, and expanding the dataset will improve results.

Hemanth, Deperlioglu, and Kose [18] provide an innovative hybrid strategy for the retinal fundus imaging-based diagnosis of retinopathy caused by diabetes. To improve diagnosis accuracy, our mixed strategy specifically integrates processing of images and deep learning. It is well known that manually interpreting these photos is a laborious, time-consuming operation requiring substantial knowledge. Medical experts turn to computer vision systems for assistance in tackling this problem, and intelligence diagnostic techniques have grown in importance. Using image processing methods like equalization of histograms and contrast-limited adaptive equalization of the histogram in the present investigation, we suggest a diagnostic method using convolutional neural networks. It is essential to enhance integrating additional imaging modalities, conducting large-scale clinical validation, and developing real-time monitoring capabilities.

To determine whether certain actions may be made to improve efficiency and solution quality, use a variety of image processing techniques. A prompt evaluation and therapy are required for diabetic retinopathy in order to prevent visual loss. Since they are concealed in minute and subtle shapes beneath the eye's structure, the medical condition's lesions are challenging to detect. Maaliw et al. [19] built an efficient process to extract pertinent features utilizing a variety of preparation methods, a visual segmentation design (DR-UNet) that has an impressive spatial pyramid pool, and an attention-aware neural convolutional networks with multiple ResidualNet-based sections. Experimental findings show that our system's precision for segmentation is 87.10% (intersection over union) and 84.50 % (dice similarity coefficient). The gradual converging of training/validation loss and accuracy further supported the claim that the 99.20% classification performance outperformed prior systems. In order to more accurately diagnose the illness in both its early and severe phases, this investigation has the potential to complement conventional diagnostics. Determine the severity of DR and create an improved framework going forward.

Diabetics must find Diabetic Retinopathy (DR) early to reduce their chance of going blind. Numerous research show that Deep Convolutional Neural Network (CNN)-based

methods are efficient for enabling automated DR identification via categorization of patient retinal pictures. In order to assist their CNN training, these techniques often rely on an enormous data set made up of retinal pictures with predetermined categorization labels. Finding sufficient accurately labeled pictures to serve as model training examples, nevertheless, is not always simple. In addition, as a CNN gets deeper, training it takes greater time and is more probable to result in over fitting, particularly if you utilize a big training dataset. In order to categorize retinal pictures, it is important to investigate a more straightforward CNN-based method that is still successful on tiny data sets. W. Chen et al [20] proposes a method for classifying retinal images that integrates multi-scale shallow CNNs. Research on open-source datasets demonstrates that, when compared with existing representational combined CNN learning algorithms, the suggested method can increase classification accuracy by 3% for short datasets. In comparison to other typical techniques like conventional CNN, LCNN, and VGG16noFC on a larger dataset, the performance of the integrated shallow CNN model will be enhanced by the modification of picture samples and repeated dataset sampling.

The limitations faced by current methods in detecting and diagnosing diabetic retinopathy (DR). The existing approaches, including deep learning techniques like Convolutional Neural Networks (CNNs), encounter challenges in categorizing the various phases of DR due to operational costs and difficulty in capturing highly nonlinear information. These methods also vary in terms of efficiency, resource utilization, and accessibility, with some relying on specialized hardware and complex models. The need for extensive datasets, lack of model explainability, and the importance of clinical validation further hinder the development of accessible and accurate diagnostic tools, particularly in resource-constrained healthcare settings.

III. Problem Statement

Diabetic retinopathy (DR) poses a significant risk to vision, leading to blindness if not diagnosed and treated promptly. The conventional manual examination of retinal images for DR diagnosis is time-consuming, error-prone, and relies heavily on the expertise of medical professionals [20]. Existing computer vision engineering approaches, including those utilizing deep learning techniques like Convolutional Neural Networks (CNNs), face challenges in properly categorizing the various phases of DR due to operational costs and difficulty in capturing highly nonlinear information [16]. Furthermore, the current methods vary in terms of efficiency, resource utilization, and accessibility [17], with some relying on specialized hardware and complex models. The necessity for extensive datasets, lack of model explainability, and the importance of clinical validation further hinder the development of accessible and accurate diagnostic tools, especially in resource-constrained healthcare settings. As the number of diabetic patients increases, there is a pressing need to overcome these limitations and devise more efficient, accessible, and accurate methods for the early detection and diagnosis of diabetic retinopathy, ultimately improving patient care and outcomes we proposes

IV. Proposed African Buffalo Optimization Based hybrid GAN -BiGRU

The proposed African Buffalo Optimization (ABO) based hybrid Generative Adversarial Network (GAN) and Bi-directional Gated Recurrent Unit (BiGRU) model represents a novel approach for diabetic retinopathy detection. ABO is integrated into the model to optimize its performance by fine-tuning parameters, enhancing its accuracy in identifying diabetic retinopathy. The hybrid architecture combines GAN's proficiency in extracting complex features from retinal images with BiGRU's sequential information processing capabilities. This synergistic interaction, augmented by ABO, result in a comprehensive and efficient model, showcasing the potential of bio-inspired optimization techniques in advancing the accuracy and reliability of diabetic retinopathy diagnosis. Fig. 1 demonstrates proposed method.

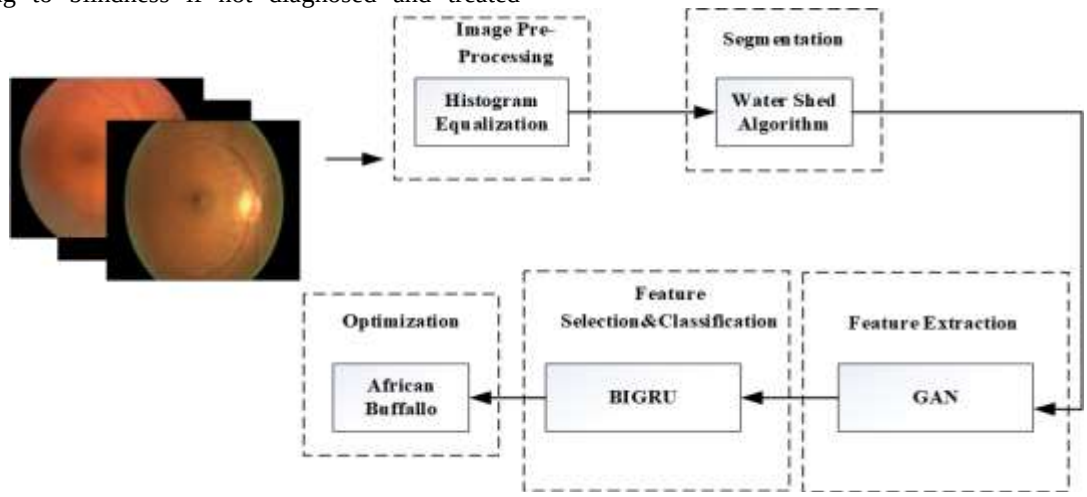

Fig. 1. Proposed ABO with GAN-BIGRU.

A. Datasets

Data set received from the Kaggle coding website (https://www.kaggle.com), which comprises over 80,000 images, each with an approximate resolution of 6 million pixels and various scales of retinopathy. To effectively process this dataset images are resized and conducted our deep learning experiments using a high-end GPU, specifically the NVIDIA K40c. This GPU is equipped with 2,880 CUDA cores and is supported by the NVIDIA CUDA Deep Neural Network library (cuDNN) for GPU-accelerated machine knowledge. To facilitate the training process, This research leveraged the capabilities of the Keras deep learning package (http://keras.io/) with Theano as the machine learning backend (http://deeplearning.net/software/theano/). This choice was made due to the availability of excellent documentation and the advantage of shorter calculation times. The performance achieved was remarkable. In fact, our system can classify an image in a mere 0.04 seconds, providing the potential for real-time feedback to benefit patients [21].

B. Image Processing

Image preprocessing in the context of image analysis involves a series of techniques to enhance image quality and make it more suitable for subsequent analysis. Histogram equalization is a specific method used to improve contrast in images. It works by redistributing pixel intensities across the entire range, resulting in an image with enhanced contrast, which can be particularly useful for improving the visual quality of images and making them more amenable to various image analysis tasks.

1) Histogram equalization: It remains one of among the most popular methods for enhancing the clarity and quality of photographs that go through processing. The goal image's histogram's range of motion is increased to accomplish this. The HE quickly converts the original image's irregular gray levels into the resulting image's consistent level of gray. The produced image has a homogeneous pattern of gray levels as a result. It is therefore reasonable to say that the HE is used to generate an even histogram. Finally, HE delivers a new intensities value for each pixel depending on its prior intensity level. The visual appeal of the picture is enhanced and its histogram is dispersed across a larger range since the histogram for low-contrast images is narrow and focused near the middle of the gray scale. The HE improves the brightness of the image by flattening and stretching the given data's histogram's range of motion.

The following theoretical approach to HE can help us understand greater detail regarding it:

It is feasible to think about a digital picture $I(i,j)$ with X total pixels and a grayscale between [0, K'-1]. Following there, an equation may be used to determine the density function probability of the associated picture in Eq. (1)

$$p(k') = \frac{n_{k\prime}}{X}, \text{ for k'=0,1,……K-1} \quad (1)$$

where $n_{k\prime}$ is the overall amount of grayscale pixels k n the picture. Additionally, Eq. (2) may be used to determine the image's (i,j) cumulative distribution function as shown in Eq. (2)

$$B(k') = \sum_{m=0}^{k\prime} P'_m \text{ for k'=0,1,…..K-1} \quad (2)$$

By taking into account the results of the cumulative distributions function. A level of input k is matched with a level of output k by$HE_{k\prime}$ may be used to do this in Eq. (3)

$$HE_{k\prime}=(K-1).B_{k\prime} \quad (3)$$

As a consequence, eqn may be used to determine the gain $HE_{k\prime}$ at the output level for the typical HE in Eq. (4)

$$\Delta HE_{k\prime}=HE_{k\prime}-(HE_{k\prime}-1)=(K-1).P'(k) \quad (4)$$

It is feasible to show that the rise in the level of of $HE_{k\prime}$'is proportionate to the likelihood of the corresponding value k in the setting of the initial picture by taking into account the linked equations. Explains the HE procedure as it appears over the histogram data in short. For photos with widely spaced tonal zones, HE is highly helpful in enabling the observation of images with a very light backdrop and a dark foreground. Expanding out the disparity between neighboring regions, that enables making noticeable the variations within the processing regions, enables the HE to reveal concealed data inside a picture.

C. Segmentation using Watershed Algorithm

The watershed method is guided by the probability maps, which improves the segmentation process' accuracy and capacity to discern among various sections of the picture. This method helps in the precise delineation of tumor borders in healthcare imaging applications and efficiently handles the problem of over-segmentation, which has become a prevalent issue in segmenting image assignments is given in Eq. (5) (6) and (7)

$$\text{Entity Part} = \{\text{Locality} \mid \text{Strength}(\text{Locality}) \geq \text{threshold}\} \quad (5)$$

$$\text{Threshold} = \min(\text{Optimistic}) + \left[\max(\text{Optimistic}) - \min(\text{Optimistic})\right] \times \text{Rate} \quad (6)$$

$$\text{Optimistic} = \{\text{Intensity} \mid \text{Intensity} \geq \text{mean}(\text{Intensities})\} \quad (7)$$

‘"Rate" is a number between 0 and 1, whereas "Optimistic" refers to the bright portion of an AO-SLO picture. Additionally, the backdrop markers were set to match the findings from local morphology processing, while the remaining region was assigned to identifiers for an unknown location. Utilizing the previously described contour-length threshold-based technique, the marker-controlled watershed segment technique was performed repeatedly at an accelerating pace till no conjunction-containing areas were found. With such cycles, every region's contour-length is below the cut-off value of one cone photoreceptor cell's contour-length, eliminating the conjunction-containing areas. Ultimately, all marker-controlled watershed segmentation rectangles are added to the outcomes of the regional morphology process. provides an illustration of the outcomes of the watershed method applied to a typical picture patch; as

can be seen, the conjunction-containing patches are distinct [22].

1) GAN-based retinal vasculature extraction: A novel Pix2Pix Generative Adversarial Network (GAN) design was used in this investigation. This design, which was first presented by Ian J. Goodfellow in 2014, consists of the Generators and Discrimination sub-models. The Generator is the component that creates data samples while the Discriminator tries to distinguish between produced and actual data, putting both of these models in competition with one another. Training doesn't stop until the discriminating agent can't tell the two apart. In order to create a picture, the Generator network is given a fixed-length randomized seed noise, also known as a receptive vector. The generating method is built on top of this latent vector. For discrimination, the resultant picture and actual images are given into the discriminator. Following training, latent variables—which resemble locations within the issue's domain but are unable to be directly observed—are represented as multifaceted vector spaces termed latent spaces. High-level concepts from the raw data are captured in the latent space, which the algorithm uses to analyze events and generate fresh results.

As a model for categorization, the Discriminant separates created examples from actual samples based on the training data. In order to minimize the Discriminator's loss, the Generator and Discriminator losses are tracked throughout training. Fig. 2 shows the systematic architecture of GAN. Training improves the Discriminator's ability to discriminate between genuine and false data and the Generator's ability to produce accurate information. Upon reaching integration, the Generator automatically generates data that is almost realistic, and the Discriminator produces ½ for every input, making it unnecessary after training.

Applications for GANs may be found in many different fields, including pattern transfer, processing images, tracking traffic, and the creation of 3D objects. Visual translating, which converts a given input image into an output picture, is one important use.

There are several varieties of GANs, such as DCGAN, cGAN, Cycle GAN, and Info GAN. For picture further sampling, DCGAN employs transposition convolutional neural networks and deep convolutional nets. cGANs are appropriate for translating images to images because they let the GAN be conditionally trained using labels for classes. Similar assignments can be completed by Cycle GAN, however it can also use mismatched dataset for learning visual mappings. Comprehensible and significant representations can be learned using info GANs. A Pix2Pix GAN, a particular instance of cGAN that is frequently employed for translating images into images research, was employed in this investigation [23].

A cGAN is able to comprehend how to map from a perceived picture (x) and a random noise vector (z) to a generated image (y), expressed as Eq. (8)

$$G' = X', Z' = Y' \tag{8}$$

The cGAN's loss coefficient is shown below Eq. (9)

$$\mathcal{L}'_c\text{GAN'(G',D')}=E'_{(X',Y')}[\log D'(X',Y')] + E'_{(X',Z')}[\log(1 - D'(X', G'(X',Z')))] \tag{9}$$

In this case, the discrimination coefficient D tends to raise the previously indicated function, whereas the generator G tends to diminish it. An unconditionally version is applied to the GAN loss in order to compute the consequences of conditioning D, as can be shown below in Eq. (10)

$$\mathcal{L}\text{GAN'(G',D')}=E'_{(Y')}[\log D'(Y')] + E'_{(X',Z')}[\log(1 - D'(G'(X',Z')))] \tag{10}$$

Throughout the further sampling and downsampling processes, the Generator in the Pix2Pix GAN forms a UNet structure using a Resnet. To further reduce distortion, a reduction function is implemented in G as follows $\mathcal{L}'_{L1'}$ in Eq. (11)

$$\mathcal{L}'_{L1'(G')}=E'_{(X',Y',Z')}[[\|\text{Y'-G'(X',Z')}\|]] \tag{11}$$

Having a patch size of 70 x 70, the Discriminators is a patchGAN. The Pix2Pix GAN's ultimate loss value is represented by a calculation that combines the cGAN loss with the $\mathcal{L}'_{L1'(G)}$ loss. The weighting of the)) loss function is determined by the parametric λ, which is as follows in Eq. (12).

$$G'^{*}=\text{Arg min}_{G'}\,\text{max}_{D'}\,\mathcal{L}'_{C'GAN(G',D')}+\lambda\,\mathcal{L}'_{L1'(G)} \tag{12}$$

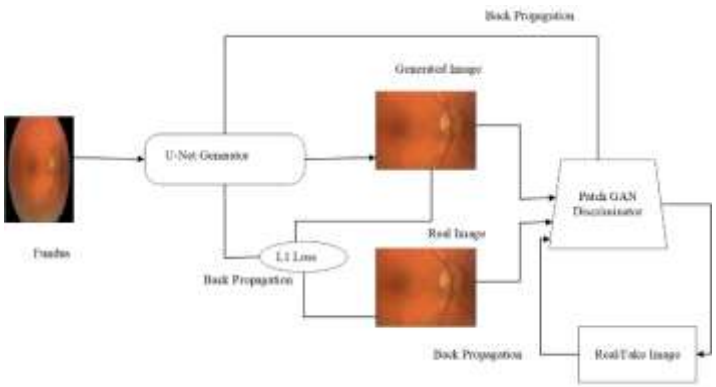

Fig. 2. GAN architecture.

D. BiGRU for Feature Selection and Classification

RNNs include gated recurrent units (GRUs). It is additionally suggested to address issues like long-term memory and slopes in reverse propagation, which are comparable to LSTM. Using sequential information as input and all neuron linked in a series, recurrent neural networks (RNNs) conduct recursive in the developmental directions of patterns. Cells have the capacity to simultaneously acquire data from other cells and their own past events because to the presence of cyclic components in the hidden layer. As a result, storage and shared parameters are features of an RNN. RNN also performs better when training nonlinear features from serialized data [24]. Researchers offered LSTM that has the ability to acquire the correlation knowledge among lengthy immediate sequences of data, as a solution to the issue of

RNN gradient fading while able to not understand lengthy-term historical load attributes. GRU had been developed recently as a solution to the issue of LSTMs having excess parameters and a sluggish convergence rate [25]. The GRU is an LSTM variation that has fewer variables with greater convergence ability while yet retaining decent learning outcomes. On the inside, the GRU model is made up of updated gates and resetting gates. In contrast to LSTM, GRU substitutes an updated gate for inputs and forgetting gates, wherein the updated gate denotes the effect of the concealed layer of neurons' output data from a prior instant on their current state. The impact's degree is higher while the latest gate value is higher. The disregard level of the buried layer neuron output at the prior instant is represented by the resetting gate. A smaller amount of data is disregarded as the reset gate value increases. The hidden layer unit A can be calculated by the following Eq. (13) to Eq. (15)

$$b_t = \sigma(A_Z.[c_{t-1}, y_t]) \quad (13)$$

$$m_t = \sigma(A_m.[c_{t-1}, y_t]) \quad (14)$$

$$\widetilde{c_t}=\tanh(A.[m_t * c_{t-1}, y_t]) \quad (15)$$

$$c_t=(1-b_t)* c_{t-1}+b_t * c_t \quad (11)$$

A_Z , U_Z and U are all training parameters matrices, while b_t and m_t are the updating gate and resetting gate, correspondingly. Tanh is the hyperbola tangent value. The resetting gatem_t, the layer that is hidden, the neuron's output c_{t-1}, the currently inputted y_t the trained parameter matrices, and U all work together to establish the candidate activation state$\widetilde{c_t}$ at the present instant.

The ability of the BiGRU network to understand the connection among factors that have influenced previous and future demands and the current load makes it easier to extract the deep characteristics of load data. Fig. 3 shows BIGRU Architecture in [26] BIGRU architecture is displayed in Fig. 3

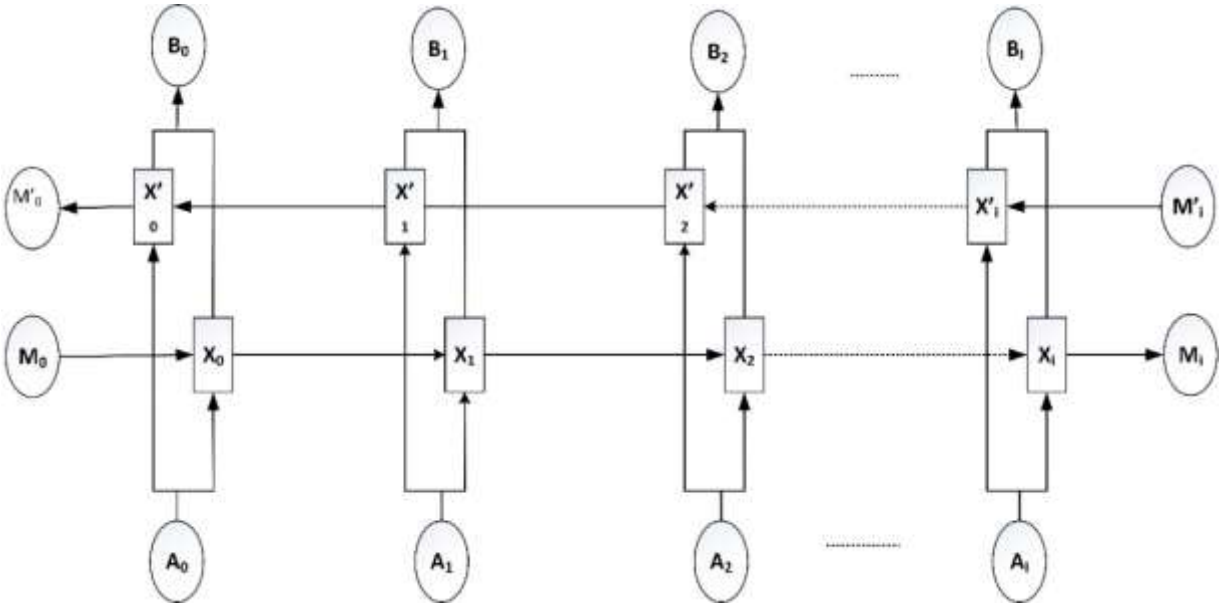

Fig. 3. BIGRU architecture.

E. African Buffalo Optimization Algorithm

The African buffalo's skill is enhanced by its place of searching in the African Buffalo Optimization technique. It is widely used to identify buffaloes by where they are and the sounds they make ('Waa' and'maa'). Additionally, studying aspects will help in the motion of the buffalo. The 'Waa' and'maa' sounds are represented by the letters wn and mn respectively. Using the formula, cooperative productivity is clearly specified in Eq. (16).

$$mn + 1 = mn + le1(cemax - wn) + le2(cdmaxn - wn) \quad (16)$$

where, mn and wn stand for the nth buffalo's discovery and extraction moves, respectively (n=1, 2, 3, N). The variables for learning $le1$are $le2$. In (1), $cemax$ is the herd's optimal fitness level and $cdmaxn$ is each buffalo's optimal fitness level is Update the place of the buffalo in ($cemax$ and$cdmaxn$) appears to be a part of the description provided for the African Buffalo Optimization algorithm. However, this statement lacks specific information or equations to clarify how the update process is performed. To provide a more accurate response, I would need additional details or equations specifying how the update process is carried out in Eq. (17)

$$wn + 1 = 2(wn + wn) \quad (17)$$

Three main components: (mn+1) the remembrance part, whereby the animals pay attention to being moved from their original location (mn). Broad memory ability is shown in their nomadic lifestyle, which is an essential tool for buffalos. The cooperative traits of buffalo are represented in the next section, $le1$ ($cemax - wn$). Buffalos can trail the locations and are effective transmitters in every iteration. The last equation, $le2$ ($cemax - wn$), reveals the superior intellect of buffaloes. They are able to compare their present position to their old, most productive job.

Algorithm 1: **Pseudocode of African Buffalo Optimization (ABO)**

Initialize the population of buffalos randomly;

Evaluate the fitness of each buffalo in the population;

Repeat until convergence:

for each buffalo in the population:

Select a random buffalo from the population;

if (fitness of the selected buffalo > fitness of the current buffalo):

Move towards the selected buffalo based on position update equation;

Perform boundary checks to ensure that the buffalo stays within the search space;

Evaluate the fitness of the updated buffalo;

Update the best solution found so far;

End Repeat

Return the best solution found;

V. Result and Discussion

The innovative approach presented in this study for diabetic retinopathy identification leverages a hybrid Generative Adversarial Network (GAN) and Bi-directional Gated Recurrent Unit (BiGRU) model, refined through the application of the African Buffalo Optimization algorithm. By capitalizing on the GAN's proficiency in extracting intricate features from retinal images, the model achieves an enhanced capacity to discern subtle patterns indicative of diabetic retinopathy. The crucial aspect of feature extraction is addressed by the GAN, revealing concealed information essential for precise diagnosis. Subsequently, the BiGRU component effectively manages temporal relationships, facilitating comprehensive information absorption from the extracted features. The amalgamation of GAN's feature extraction and BiGRU's sequential information processing engenders a synergistic synergy, endowing the model with a profound understanding of retinal images. Furthermore, the utilization of the African Buffalo Optimization technique fine-tunes the model's parameters, optimizing its performance and resulting in an impressive accuracy rate of 98.5% in diabetic retinopathy detection. This Python-based study not only attests to the model's exceptional accuracy but also underscores its remarkable efficacy in advancing the field of diabetic retinopathy diagnosis.

A. Performance Evaluation

Precision is the most often used approach for measuring categorization efficacy among the key assessment measures. By counting the percentage of test datasets that a classifier properly classifies, precision evaluates a classifier's accuracy. However, focusing entirely on accuracy might be constrained because it occasionally doesn't result in the best choices. Researchers have included others such as accuracy, recall, precision, and F1-score, to fully assess the classifier's performance. These measurements are each defined as follows: Accuracy:

The accuracy of the model is assessed using confusion metrics, a widely used statistic that assesses the model's performance in classification tasks. The percentage of instances that were properly detected out of all the cases taken into consideration is measured by the accuracy metric (ACC). This parameter, which is frequently presented as a percentage, shows how precisely the classification algorithm can pinpoint the pertinent circumstances. Accuracy in this scenario is determined as Eq. (18)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (18)$$

Wherein FP stands for False positives, TP represents for true positives, TN represents for true negatives, and FN is for false negatives.

Precision (P), which is the proportion of true positives to all positively identified instances, serves as a key assessment indicator in the present investigation. This is the proportion of persons correctly categorized as having the illness amongst every person, as Eq. (19)

$$Precision = \frac{TP}{TP+FP} \quad (19)$$

Recall (R), which in this case stands for the proportion of true positives correctly identified by the model, is also quite important. Recall is an important consideration when evaluating the efficacy of the framework in the framework of this study in Eq. (20)

$$Recall = \frac{TP}{TP+FN} \quad (20)$$

These criteria are essential for assessing how well a DR categorization system is working. They are used to construct the F1-score, which is defined theoretically as follows and stands for the harmonic mean of accuracy and recall:

$$F1-score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (21)$$

This F1-score serves as a crucial barometer of how well the system can identify people who are impacted by Drive Stages of DR Classification Results

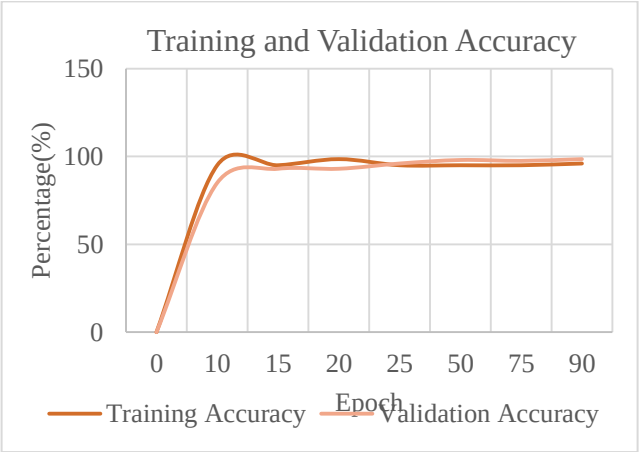

Fig. 4. Training and Testing Accuracy

The graphical depiction for the training and validation accuracy of the proposed method, ABO based GAN-BIGRU Fig. 4 and Fig. 5 illustrates the performance of the model during the training process. The validation accuracy curve demonstrates how effectively the algorithm extends to new data, whereas the training accuracy curve often demonstrates the extent to which the model learns from training data. These curve' divergence and convergence patterns reveal information about the model's capacity to identify characteristics and generate precise predictions. In order to evaluate the model's performance and make sure that it does not over-fitting the information used for training, it is crucial to keep an eye on these efficiency curves.

A crucial visual depiction of the process of learning for the ABO based GAN-BIGRU is the process of training and validation loss. The model's capacity to minimize error during training and to adapt to new data during verification is shown by these loss curves. The validity loss curve demonstrates how well the algorithm extends whereas the training loss curve normally lowers as the system improves from the training data. By observing these curves, you can assess the simulation's capability to fitting the data without overfitting, identify convergence or divergence patterns, and determine whether adjustments are needed in the training process, such as modifying hyperparameters or adjusting the model architecture to improve its overall performance.

Fig. 6 displays Enhancing the fitness of the African Buffalo Optimization (ABO) algorithm involves a multifaceted approach, including parameter tuning, hybridization with other optimization methods, adaptive strategies, local search techniques, problem-specific customization, parallelization, thoughtful fitness function design, adjusted termination criteria, robustness enhancements, and rigorous experimental validation. By systematically applying these strategies, the ABO algorithm can be tailored to address a wide spectrum of optimization challenges and improve its capacity to converge to optimal or near-optimal solutions effectively.

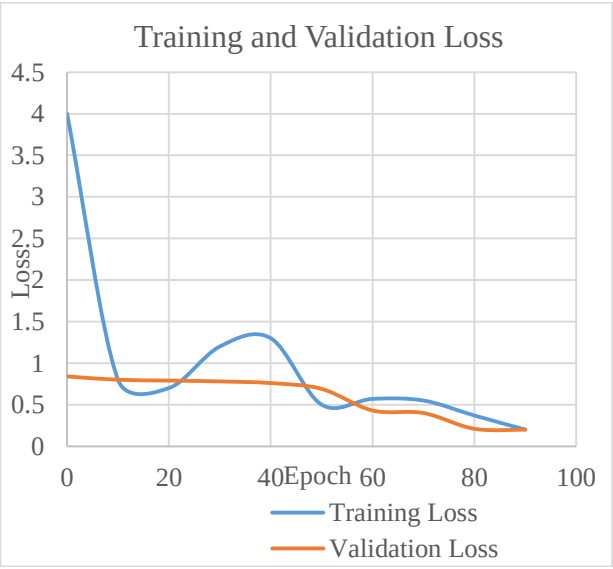

Fig. 5. Training and testing loss.

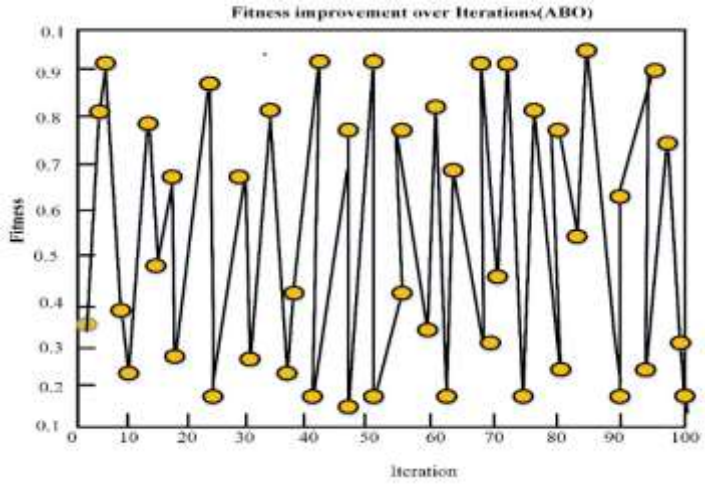

Fig. 6. Fitness improvement over iterations (ABO).

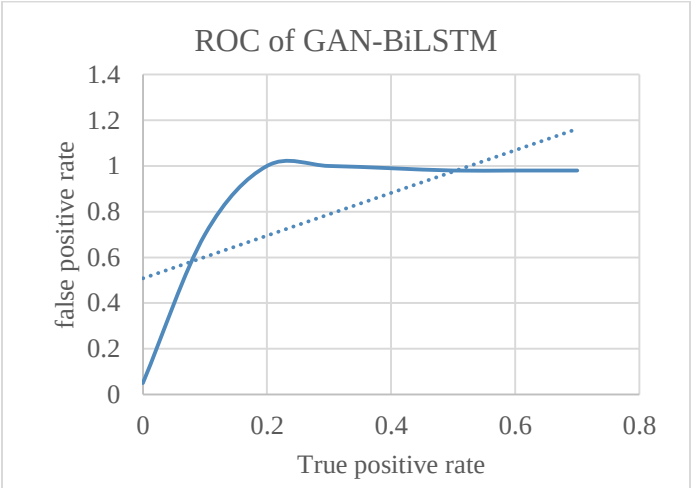

Fig. 7. ROC curve for proposed ABO-based GAN-BIGRU.

Fig. 7 symbolizes the GAN-BiGRU model for diabetic retinopathy identification using the ABO (African Buffalo Optimization) Based ROC curve exhibits the algorithm's capability to discriminate between individuals with and without diabetic retinopathy across different categorization criteria. The area under the curve (AUC) value will increase as the ROC curve gets closer to the top-left corner of the plot, suggesting an algorithm with good diagnostic effectiveness and high true positive rates and low false positive rates. The properties of the dataset and the model projections will determine the precise curve shape and AUC value.

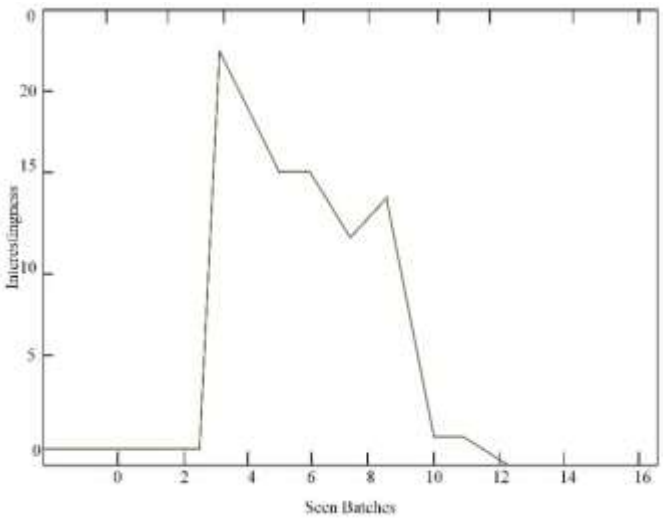

Fig. 8. An illustration of interestingness during instruction.

Fig. 8 illustrates interestingness during instruction According to the statement; interest is maintained throughout the training period. The interestingness value stays non-zero while the model learns from the training data and modifies its parameters, suggesting continuous updates that support the model's learning process. This continuous attention is probably related to how the model has adjusted to the subtleties and patterns found in the training set.

Table I compares the suggested strategy with several current methods in terms of performance measures. This tabled data provides a summary of the major assessment criteria where the suggested technique outperforms its predecessors. It is a useful resource for comprehending the better performance and efficacy of the suggested strategy in the particular application or study topic.

TABLE I. ASSESSMENT OF PERFORMANCE METRICS OF SUGGESTED METHOD WITH FURTHER EXISTING APPROACHES

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Alex Net[27]	97.9	96.23	95.42	795.82
Random Forest [28]	94.1	97.6	94.3	95.9
VGG-NIN[15]	94.20	90.0	98.0	94.0
Proposed ABO Based GAN-BIGRU	98.5	98.54	96.3	97.8

Fig. 9. Visual representation comparing the proposed method with existing approaches.

Fig. 9 shows comparison of proposed method with existing methods. Alex Net (achieved an accuracy of 97.9%, with a precision of 96.23%, a recall of 95.42%, and an F1-score of 95.82%. Random Forest exhibited an accuracy of 94.1%, with a high precision of 97.6%, a recall of 94.3%, and an F1-score of 95.9%.VGG-NIN showed an accuracy of 94.20%, with a precision of 90.0%, a notably high recall of 98.0%, and an F1-score of 94.0%. The proposed ABO Based GAN-BIGRU model achieved an impressive accuracy of 98.5%. It also demonstrated high precision at 98.54%, a recall of 96.3%, and a remarkable F1-score of 97.8%. These results highlight the varying performance of different classification models for diabetic retinopathy, with the "Proposed ABO Based GAN-BIGRU" model showing the highest overall performance across all metrics.

TABLE II. RETINAL IMAGE DATASETS AND THEIR ATTRIBUTES

Dataset Name	DR Lesion Annotation	Vessel Segmentation	Resolution	Number of Images
DRIVE	(NO DR)	YES	896×896	10 train + 10 test
Kaggle	Only severity levels	YES	1281×1281	36.1k train + 54.6k test
IDRiD	Pixel-wise lesion segmentation & severity levels	NO	4289×2849	IDRiD Pixel-wise lesion segmentation No 4289×2849
Retinal-Lesions	Pixel-wise lesion segmentation	NO	583×575	338 train + 1257 test
FGADR	Lesion annotation in circle & severity level	YES	1280×1280	500 train + 1343 test

Retinal image datasets and attributes are shown in Table II Several retinal image datasets with diverse attributes have been instrumental in advancing diabetic retinopathy research. The DRIVE dataset, characterized by 10 training and 10 testing images, focuses on vessel segmentation with a resolution of 896x896 pixels. The Kaggle dataset, comprising 36.1k training and 54.6k testing images, annotates only severity levels and includes vessel segmentation at a resolution of 1281x1281 pixels. IDRiD offers pixel-wise lesion segmentation and severity levels with a substantial resolution of 4289x2849 pixels. The Retinal-Lesions dataset features pixel-wise lesion segmentation in 338 training and 1257 testing images with a resolution of 583x575 pixels. Finally, the FGADR dataset provides lesion annotation in circles, along with severity levels, and incorporates vessel segmentation in 500 training and 1343 testing images at a resolution of 1280x1280 pixels. These datasets play a crucial role in fostering the development and evaluation of diabetic retinopathy detection models, each offering unique challenges and opportunities for research and advancement in the field.

B. Discussions

The hybrid Generative Adversarial Network (GAN) and Bi-directional Gated Recurrent Unit (BiGRU) model, fine-tuned with the African Buffalo Optimization algorithm, represents a notable advancement in diabetic retinopathy detection. By combining GAN's proficiency in extracting intricate features from retinal images with BiGRU's effective handling of temporal relationships, the model achieves an impressive 98.5% accuracy rate. The incorporation of the African Buffalo Optimization algorithm further optimizes the model's parameters, showcasing the potential of bio-inspired optimization techniques in enhancing the performance of deep learning models for medical image analysis. This integrated approach not only underscores the significance of feature extraction and temporal considerations in diabetic retinopathy diagnosis but also highlights the promising synergy achievable through the convergence of diverse neural network architectures and optimization strategies.

VI. CONCLUSION AND FUTURE WORK

In conclusion, the hybrid GAN-BiGRU model, fine-tuned with the African Buffalo Optimization algorithm, presents a robust solution for diabetic retinopathy detection, achieving an impressive accuracy rate of 98.5%. This study underscores the effectiveness of combining advanced feature extraction capabilities with temporal information processing, showcasing the synergy between GAN and BiGRU architectures. The integration of the African Buffalo Optimization algorithm further refines the model's parameters, emphasizing the potential of bio-inspired optimization in enhancing diagnostic accuracy. For future work, exploring the model's generalizability across diverse populations and investigating its applicability to real-world clinical settings would be valuable. Additionally, continued efforts to interpret the model's decisions and address potential biases in the dataset could contribute to its clinical adoption. Further refinement and validation through large-scale multi-center studies could solidify the model's potential as a valuable tool in early diabetic retinopathy diagnosis.

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