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An Intelligent Crow Search Optimization and Bi-GRU for Forest Fire Detection System Using Internet of Things

Syed Abdul Moeed[1], Bellam Surendra Babu[2], M. Sreevani[3], B. V. Devendra Rao[4], R. Raja Kumar[5] and Gouse Baig Mohammed[6†]

[1]Department of Computer Science and Engineering, Kakatiya Institute of Technology and Science, Warangal, Telangana, India
[2]Department of Computer Science and Engineering, KLEF (Koneru Lakshmaiah Education Foundation (Deemed to be University), Vaddeswaram, Andhra Pradesh, India
[3]Department of Computer Science and Engineering, BVRIT Hyderabad College of Engineering for Women, Hyderabad, India
[4]PTO & Associate Professor (AcSIR), CSIR-IICT, Tarnaka, Hyderabad, India
[5]Department of Computer Science and Engineering, Rajeev Gandhi Memorial College of Engineering and Technology, Nanadyal, Andhra Pradesh, India
[6]Department of Computer Science and Engineering, Vardhaman College of Engineering, Shamshabad, Hyderabad, India
†Corresponding author: Gouse Baig Mohammed; gousebaig@vardhaman.org

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ABSTRACT

Natural ecosystems have been facing a major threat due to deforestation and forest fires for the past decade. These environmental challenges have led to significant biodiversity loss, disruption of natural habitats, and adverse effects on climate change. The integration of Artificial Intelligence (AI) and Optimization techniques has made a revolutionary impact in disaster management, offering new avenues for early detection and prevention strategies. Therefore, to prevent the outbreak of a forest fire, an efficient forest fire diagnosis and aversion system is needed. To address this problem, an IoT-based Artificial Intelligence (AI) technique for forest fire detection has been proposed. This system leverages the Internet of Things (IoT) to collect real-time data from various sensors deployed in forest areas, providing continuous monitoring and early warning capabilities. Several researchers have contributed different techniques to predict forest fires at various remote locations, highlighting the importance of innovative approaches in this field. The proposed work involves object detection, which is facilitated by EfficientDet, a state-of-the-art object detection model known for its accuracy and efficiency. EfficientDet enables the system to accurately identify potential fire outbreaks by analyzing visual data from the sensors. To facilitate efficient detection at the outbreak of forest fires, a bi-directional gated recurrent neural network (Bi-GRU-NN) is needed. This neural network architecture is capable of processing sequential data from multiple directions, enhancing the system's ability to predict the spread and intensity of fires. Crow Search Optimization (CSO) and fractional calculus are used to create an optimal solution in the proposed crow search fractional calculus optimization (CSFCO) algorithm for deep learning. CSO is inspired by the intelligent foraging behavior of crows, and when combined with fractional calculus, it provides a robust optimization framework that improves the accuracy and efficiency of the AI model. Experimental analysis shows that the proposed technique outperformed the other existing traditional approaches with an accuracy of 99.32% and an error rate of 0.12%. These results demonstrate the effectiveness of the integrated AI and optimization techniques in enhancing forest fire detection and prevention. The high accuracy and low error rate underscore the potential of this system to be a valuable tool in mitigating the risks associated with forest fires, ultimately contributing to the preservation of natural ecosystems.

INTRODUCTION

The world is facing a major threat of climatic change. This is mainly due to rapid industrialization and globalization efforts made during the past decade. Forest fires are more prevalent among many nations of the world due to the alarming rise of global warming and deforestation. Forest fires result in increased economic loss and ecosystem damage, resulting in an unprecedented catastrophe to human lives. Forest fires are usually induced by man-made activities and environmental disasters. Due to these factors, forest fires are rapid and tough to subdue. Utilization of sensor-based forest fire detection systems performs efficiently, but the deployment and coverage become enormously difficult (Chen et al. 2007, Zhang et al. 2020, 2018, Yu et al. 2005, Zhang et al. 2009). The rapid spread of forest fires not only affects the nearby community, it also causes health hazards and fatalities. This also results in environmental pollution that would harm the entire city. In addition, even the firemen cannot be able to access and calculate the amount of damage caused by forest fires. It is also evident that due to environmental speculation, limited coverage of infrared and ultraviolet detectors (Kang et al. 2013, Lee et al. 2001) will not provide any support in remote areas. Forest fires of long-range can be easily detected by using satellite remote sensing (Botta et al. 2016). However, the detection of lesser fires is much tougher to diagnose at remote locations. Due to greenhouse emissions, global warming, and climatic change, hydrological patterns get altered, resulting in unforeseen greenhouse gas concentrations.

Technological advancements in image processing and computer vision have a critical impact on addressing the problem of forest fires which attracts several researchers. Especially the Internet of Things (IoT) and information and communication technology (ICT) spurn remote sensing capabilities using VANETs, UAVs, and drones (Rathore et al. 2016, Rajkumar & Kumar 2024a, 2024b). Since IoT devices are resource-constrained and dynamic, they are capable of forming a network by making their own decisions. These devices can be disintegrated at remote locations possessing limited storage and energy. IoT supports a wide variety of applications pertaining to security, machine vision, image processing, etc. (Fernandes et al. 2004). IoT unleashed the birth of smart cities by connecting sensors, detectors, transportation systems, home appliances, and every indoor and outdoor object via the internet to make dynamic decision-making and learning potential on its own. Therefore, appropriate conceptions and rules are supposed to be made in terms of objects and participants (Kyriazis et al. 2013). This will generate a new arena by providing various research opportunities in case of heterogeneous situations. Several policies relating to energy, infrastructure environment, and society are supposed to be enacted utilizing IoT (Bui et al. 2012). IoT devices also capture a large amount of information which contains hidden insights to make decisions by finding patterns using data analytics. Smart cities coagulate smart services, welfare programs, and digitization by shifting access to objects remotely. Therefore, these advancements are facilitated with the help of the smart city operating systems, which capture a huge amount of data about the physical location of where the IoT devices are installed. The data gets stored on a public cloud (Farrell et al. 2018). This amounts to a large amount of big data, and with the help of AI, real-time simulation models to study human behavior and decision-making can be enacted. This leads to sensitive policy-making by private as well as government institutions. Several case studies have been adapted to counter the effect of forest fires, and bushfires have been investigated (Lai et al. 2018). Models of deep learning find a wide application in the arena of forest fire detection and management study.

MOTIVATION

Forest Fires cause huge destruction to the livelihood of the people, environment, climate, animals, and other living beings on the planet. Since forest fires possess a global economic significance, several technologies and techniques are being put forth for their diagnosis and aversion. Advancements made in Computer Vision (CV), Artificial Intelligence (AI), and the Internet of Things (IoT) (Tandon & Tandon 2019) invoke its use for collecting data and predicting forest fires. This provokes the thought to develop a deep learning-based real-time object detection model for forest fire detection. Since AI performs much better at feature learning and attributes, they perceive a higher amount of semantic information than human capabilities. Hence deep learning finds a wide use even in the field of disaster and fire detection industry.

MAJOR CONTRIBUTIONS

Several applications and technologies have been proposed by various researchers to detect and prevent forest fires using AI and IoT. The proposed work involves the following major contributions, which are defined as follows:

- This study emphasizes the detection and prediction of outbreaks of forest fires with the help of deep learning techniques. The proposed work involves the use of the real-time object detection model called EfficientDet (Tan et al. 2020).
- Bi-GRU-NN for fire detection (Başarslan & Kayaalp 2023) and Crow Search (Thawkar & Shankar 2022). Fractional Calculus Optimization (Mahaveerakannan et al. 2023), techniques are utilized for optimizing the training parameters to obtain optimal performance.
- The proposed work involves the use of four different sets of forest fire datasets such as BowFire (BowFire 2019), FD-Dataset (FD-Dataset 2019), Forestry Images (ForestryImages 2018) and VisiFire (VisiFire 2003).
- Evaluation results obtained achieve a 99.32% accuracy rate with an error rate of 0.12%. Table 1 provides the list of abbreviations utilized in our study.

Table 1: Abbreviations utilized.

Abbreviations	Description
Bi-GRU	Bi-directional Gated Recurrent Unit
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory Networks
Bi-LSTM	Bi-Directional Long Short Term Memory Networks
DL	Deep Learning
ML	Machine Learning
IoTs	Internet of Things
AI	Artificial Intelligence
NN	Neural Network
Bi-GRU-NN	Bi-directional Gated Recurrent Unit based Neural Network
CSO	Crow Search Optimization
CSFCO	Crow Search-based Fractional Calculus Optimization
ICT	Information and Communication Technology
VANETs	Vehicular Adhoc Networks
UAVs	Unmanned Aerial Vehicles
CV	Computer Vision
FD, ReLu	Fire Detection, Rectified Linear Unit
WSN	Wireless Sensor Networks
FFDNet	Forest Fire Detection Network
RMSProp	Root Mean Square Propagation
FN	Fog-Node
KELM	Kernel Extreme Learning Machine
EPO	Emperor Penguin Optimizer
MCU	Micro-controller Unit
DTF	Decreasing total flying time algorithm
TSA	Tunicate Swarm Algorithm
ITF	Increasing total flying time algorithm
HRA	Half regions assignment algorithm
QRA	Quarter regions assignment algorithm
TRA	Tier regions assignment algorithm
RID	Randomly-iteratively drone algorithm
SEOF	Sleep Scheduling and Energy Optimized Framework
MATLAB, TSHO	Maths Laboratory, Taylor Spotted Hyena Optimization
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
WMSNs	Wireless Multimedia Sensor Networks
IMAGENet	Image Network
VGG	Visual Geometry Group
RLSTM-NN	Recurrent Long Short Term Memory Networks based Neural Networks
OPCNN	Optimal Convolutional Neural Network
NAS	Neural Architectural Search
Bi-FPN	Bi-directional Feature Pyramid Network
PANets	Path Aggregation Networks
CIFAR	Canadian Institute for Advanced Research

PAST STUDIES OF RELEVANCE

Several Researchers have put forth various works on the detection, managing, predicting, and forecasting of forest fires. This section provides a clear-cut overview of various techniques catering to the need for forest fires, along with their benefits and limitations.

In the Chinese province of Jiangsu, a fuzzy inference-based prediction system for forest fires has been proposed (Lin et al. 2018). Their technique works based on accessing and quantifying the consequences using fuzzy inference. Fuzzification and output rating levels are utilized to deliver these parameters into a triangular fuzzy number. Their technique has been carried out by using rechargeable WSNs. Their technology successfully identified the likelihood of a forest fire with a high degree of accuracy. A Fog-assisted hierarchical data routing strategy for IoT-enabled WSN for forest fire detection has been developed by (Moussa et al. 2022), making use of an energy-efficient multi-fog node (FN) based clustered network model. By reducing communication costs, their technique preserves the energy of the sensor nodes. High efficiency of 8.23% of network lifetime and 19.02% of response time are achieved by their suggested system. However, their work has not focused on real-world sensor nodes. A WSN-based automated system for the detection of forest fires has been proposed by utilizing the FFDNet deep learning framework, which combines a modified Xception network for feature extraction with an optimizer for root mean square propagation (RMSProp) and guided filter for noise removal (Paidipatti et al. 2023). The EPO algorithm has been applied to choose the ideal parameters, and the kernel extreme learning machine (KELM) model has been used to identify forest fires. Their proposed work used FFD Dataset implemented using Python thereby achieving a high accuracy rate of 99.17%. However, their technique has to be combined with the deep ensemble fusion model to assess its performance. Using a dynamic convolutional neural network, (Zheng et al. 2023) created an application for monitoring forest fires and providing early warnings. Their proposed technique put forth a back propagation neural network fire algorithm. The forest fire image dataset has been used and is classified for feature extraction. According to a performance investigation, 84.37% accuracy is achieved in low frame rate forest fire recognition. However, their model is complex, and optimization is essential. IoT-based forest fire monitoring and early warning system was proposed (Divya et al. 2019) utilizing uses sensor- and microcontroller-based technology to identify forest fires. However, their technique has not been evaluated with the machine and deep learning algorithms. A forest fire prediction model using IoT and deep learning techniques using an MCU microcontroller node in conjunction with sensor technology (Ananthi et al. 2022). Though their system performs the prediction of forest fires, it cannot handle large amounts of big data.

A surveillance system based on drones utilizing an optimization algorithm for forest fire prevention using Decreasing total flying time algorithm (DTF), Increasing total flying time algorithm (ITF), Half regions assignment algorithm (HRA), Quarter regions assignment algorithm (QRA), Tier regions assignment algorithm (TRA), Randomly-iteratively drone algorithm (RID) has been proposed (Jemmali et al. 2023). According to experimental data, the RID algorithm performs optimally, achieving 90.03% accuracy in 0.08 seconds. A deep learning architecture based on long short-term memory networks was used to develop a fire alert forecasting model has been developed (Jamshed et al. 2022). Their technique utilized the Pakistan forest fire dataset and achieved a prediction performance of 95% accuracy. However, the performance of the model has to be improved to handle big data. To optimize the fitness parameters (Verma et al. 2021), The Tunicate Swarm Algorithm (TSA), which is based on sleep scheduling and an energy-optimized framework (SEOF), has been developed for the detection of forest fires. The experiment was conducted by using MATLAB thereby achieving a network stability of 35.3%. However, the optimization of sink placement and mobility scenarios are to be tested to enhance the performance. An early forest fire detection system utilizing machine learning, image processing, and sensor fusion technology has been proposed (Nassar et al. 2022). Their technique chose ANN, RNN, and CNN models with the IMAGENet dataset. They have achieved an accuracy of 99.5%. Nonetheless, maximizing solar energy and node energy consumption extends the network's lifespan. By creating a lightweight deep learning model, A novel hierarchical method for detecting forest fires in diverse wireless multimedia sensor networks (WMSNs) has been investigated (Kizilkaya et al. 2022). Between the sink and the edge, their suggested work increases detection accuracy and traffic efficiency by 98.28% and saves 29.94% of energy.

Nevertheless, the proposed algorithm has to be tested for E-Health platforms. An early warning classification of forest fires using bird sounds has been investigated by using a CNN model (Permana et al. 2022). The model has been chosen to classify the bird sounds and achieved an accuracy of forest fire detection of 96.43%. IMAGENet dataset has been utilized for the forest fire detection system. Using additional animal sounds can further increase accuracy. For hazy IoT environments, a convolutional neural network solution based on smoke detection has been investigated (Khan et al. 2019). VGG-16, Googlenet and Alexnet models have been utilized for their study. ImageNet dataset with their proposed model achieved an accuracy of 97.72%. The model must be made less expensive, though, because it is rather sophisticated.

A forest fire monitoring system utilizing IoT in conjunction with the Catswarm Fractional Calculus Optimization (CSFCO) algorithm was proposed (Mahaveerakannan et al. 2023). EfficientDet, an object detection model, has been chosen for the implementation where the forest fire has to be detected by using RLSTM-NN. With an error rate of 0.14%, their recommended method produced results with a precision of 98.6%. Furthermore, a smoke detection model can be developed to reduce optimization approach errors. An optimization technique based on surveillance towers, monitoring balloons, and drone technology to develop an integrated forest fire detection system has been investigated (Fuente et al. 2024). They created a mixed linear integer algorithm model to handle routing, coverage, and location decisions.

Further improvement can be made by using a meta-heuristic algorithm. An emergency adaptive routing scheme for WSN to monitor the fire hazard in emergencies has been investigated utilizing the Jacobson algorithm to achieve less end-to-end delay and average load energy (Zeng et al. 2011). The future work can be tested on industries and building fires. Gomez et al. have come up with a novel application for the early detection of forest fires using overhead power lines of WSNs. They have utilized sensor technology for the detection of forest fires. However, their work lacked novelty

Table 2: Comparative analysis of works on forest fire detection.

References	Problem Addressed	Technique Utilized	Benefits	Limitations
Moussa et al. (2022)	Detection of Forest Fires	Hierarchical Data Routing Strategy	Network Lifetime is increased by 8.23%	Real-time implementation has to be tested
Paidipatti et al. (2023)	Detection of Forest Fires	Guided Filtering, Modified Xceptron Network, Root mean square propagation (RMSProp) optimizer, Kernel Extreme Learning Machine (KELM), EPO algorithm	Accuracy 99.59%	The technique has to be tested across various scenarios
Zheng et al. (2023)	Monitoring of Fire Hazards	Emergency-Adaptive Routing Scheme	Energy Consumption is increased	The routing hole problem is yet to be addressed
Ananthi et al. (2022)	Prediction of Forest Fires	NodeMCU controller	Accuracy 97%	Training the dataset has not been considered
Jemmali et al. (2023)	Prevention of Forest Fires	Increasing total flying time algorithm (DTF, ITF), Half regions assignment algorithm (HRA), Quarter regions assignment algorithm (QRA), Randomly iteratively Drone Algorithm (RID)	Accuracy 90.3%	Dataset instances are very low, which needs to be considered
Jamshed et al. (2022)	Forecasting of Forest Fires	Long Short Term Memory Networks (LSTM)	Accuracy 95%	Several parameters concerning forests have not been considered
Verma et al. (2021)	Detection of Wild Fires	Sleep scheduling-based Energy Optimized Framework (SEOF), Tunicate Swarm Algorithm (TSA)	-	Physical obstacle between sensor nodes to withstand high temperatures during wildfires has to be improved.
Kizilkaya et al. (2022)	Detection of Forest Fires	Convolutional Neural Networks	Accuracy 98.28%, Energy saving 29.94%	The proposed work has not considered edge computing devices, Accuracy needs to be improved.
Mahaveerakannan et al. (2023)	Detection of Forest Fires	Cat Swarm Optimization, Recurrent Long Short Term Memory Networks (RLSTM)	Precision 98.6% Error Rate 0.14%	The smoke area has been left, which needs to be taken into consideration
Fuente et al. (2024)	Monitoring of Forest Fires	Mixed-integer linear programming model	Energy Cost, Distance	-
Zeng et al. (2011)	Recognition of Forest Fires	Back propagation neural network fire (BPNNFire) Algorithm	Accuracy 84.37%	Detection and performance have to be improved by using optimization algorithms.
Jayasingh et al. (2024)	Detection of Forest Fires	Optimal convolution neural networks (OPCNN) Models: CNN & J48	Accuracy 95.11%	Still, the accuracy needs to be improved

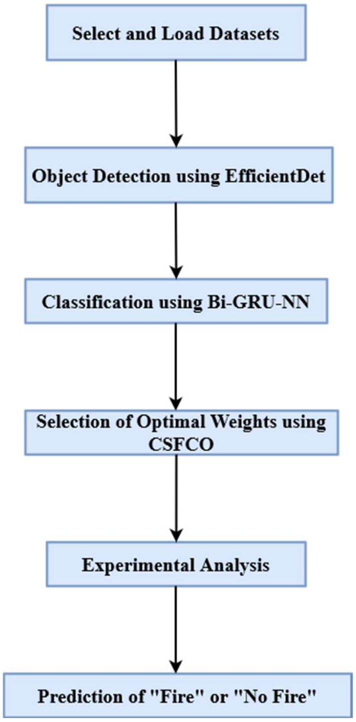

Fig. 1: Methodology of forest fire detection system.

and dataset training. An experimental method for forest fire detection employing an optimum convolutional neural network has been developed and investigated (Jayasingh et al. 2024). Their proposed model utilized a forest fire dataset implemented using Python, achieving an accuracy of 93.45%. In addition, optimal parameter selection and hybrid soft computing models provide better accuracy. Table 2 provides a comparative analysis of various works on forest fire outbreak detection, along with their advantages and limitations.

From Table 2, it is evident that the works proposed by the researchers attempted for forest fire detection achieved an accuracy of up to 99%. However, the error rate has to be minimized to a greater extent. Additionally, object detection models have to be developed to adapt to the natural ecosystem under various illumination conditions. Hence, there is a strong need to increase the optimization technique to achieve optimum performance. To achieve high detection accuracy of forest fires, our proposed work involves the use of a crow search-based fractional calculus optimization technique.

MATERIALS AND METHODS

The proposed methodology involves the use of IoT and AI for forest fire detection. To facilitate object detection remotely, the deep learning-based bi-directional gated recurrent neural network has been developed, designed, and implemented. The framework involves the use of fractional calculus-based optimization to improve the performance of the optimal parameters chosen for detection. Fig. 1 provides a depiction of the methodology involved in the Forest fire detection strategy.

Datasets Utilized

The proposed methodology used publically available datasets, which involved a combination of ground fires, trunk fires, and canopy fire images. The publicly available datasets like Bow fire, FD-Dataset, Forestry images, and Visifire are involved in our proposed work. Fig. 2 represents the datasets utilized for our proposed work. A flame, like a peat wildfire, burns the organic components that cover the ground beneath the covering. Trunks normally have one branch, but they can also possess several stems. The primary responsibilities include transportation and support for supplies. The bark's major job is to protect the basal layer, which is a live cell. A canopy is an open-sided, extending roof structure. It may be used for decorative reasons or to attract interest to a direction or part of a structure, in addition to its primary function of

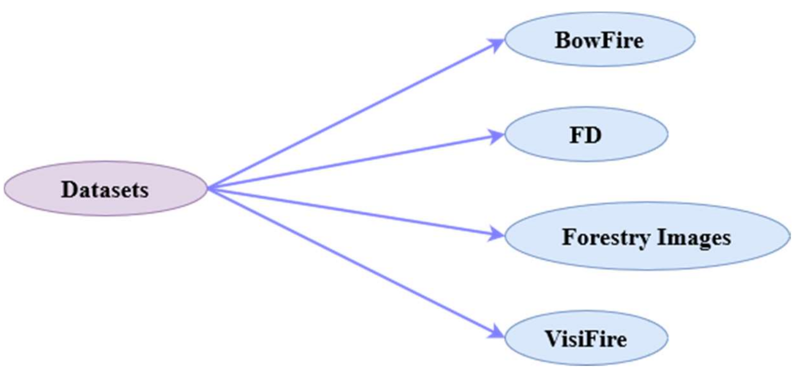

Fig. 2: Datasets utilized in our proposed work.

a. Groundfire-1 b. Groundfire-2

c. Trunk Enthusiasm d. Canopy Fire

Fig. 3 (a-d): An overview of forest fire images of the datasets.

a. Normal Forest scene-1. b. Normal Forest Division 2.

c. Normal Forest Division 3. 4. Normal Forest Division 4.

Fig. 4 (a-d): Represents the list of non-fire forestry images from the chosen datasets without any fire substances.

a. Forest Division with Sun-1.

b. Forest Division with Sun-2.

c. Forest Division with Sun-3.

d. Forest Division with Sun-4.

Fig. 5 (a-d): Represents the list of non-unit sections of forestry images with the sun from the chosen datasets incorporated with the fiery nature of a sun.

protecting from heat and moisture. Manually, the forest fire dataset has been assembled, which is combined with 10,581 photographs (2976 fire images and 7605 non-fire images) for the evaluation of our proposed work. Figs. 3-5 provide an overview of the different scenarios of our datasets.

Object Detection

The performance and accuracy of the Convolutional neural networks can be improved by the method of larger compound scaling. Since an image contains detailed information about objects it is necessary to be captured to increase the precision. In the case of larger images, deeper networks are highly required this can be induced by receptor neurons and channels to capture minute details of objects. Researchers discovered that the performance of the deeper networks from model scaling is stationed upon the baseline network. This gives rise to the development of Neural Architecture Search (NAS) to find an optimum baseline network (Datascience 2019). In summary, the NAS algorithm detects the best structures by employing Reinforcement Learning when the fitness function is provided. This leads to a new category of models of deepNets called EfficientNets. To address the challenges of multi-scale feature fusion and model scaling EfficientNets in coagulation with Bi-directional Feature Pyramid Network (BiFPN) a new object detection model has been built called EfficientDets. EfficientDet makes use of BiFPN for a compounded model scaling strategy that adapts frameworks, depth, width, and resolution. EfficientNet models showed high accuracy with ImageNet and CIFAR-100 datasets. Figs. 3-5 provide the model of the EfficientDet architecture. EfficientDet is backed by the high-performance EfficientNets, which provides the model with the capabilities it needs to comprehend the subtle differences between various kinds of forest fires. All the fragments of the developed framework calculate a variety of attributes such as warmth, lighting, movement, moisture, and altitude. One characteristic that sets forest fires apart is that they occur in open spaces with strong winds. Conversely, they are fueled by highly combustible compounds such as flammable lignocellulose, which is a dried leaf. Sometimes perilous chemicals, fire, and air induce forest fires.

Secondly, EfficientDets utilize PANet (Wang et al. 2019) variant such as Bi-FPN for fusing the feature maps with various resolutions and receptive fields outputted by the last three stages of the backbone network to enhance the process of feature extraction (Liu et al. 2018). Bi-FPN provides quick and multi-scale feature fusion. From a single view of any dimension, a learning technique called a Feature Pyramid Network, or FPN, generates proportionately scaled image features at several levels in a fully performing fashion. This process is independent of the layered patterns that underlie it. There are several more layers situated behind the skull and vertebrae. They are employed to acquire different feature maps constructed on prior phases. Among other options, the cervical part could be an FPN, PANet, or Bi-FPN. With the aid of learnable weights that enable the net to determine the relative importance of different input features, the Bi-FPN regularly uses multi-scale feature fusion. In addition to class

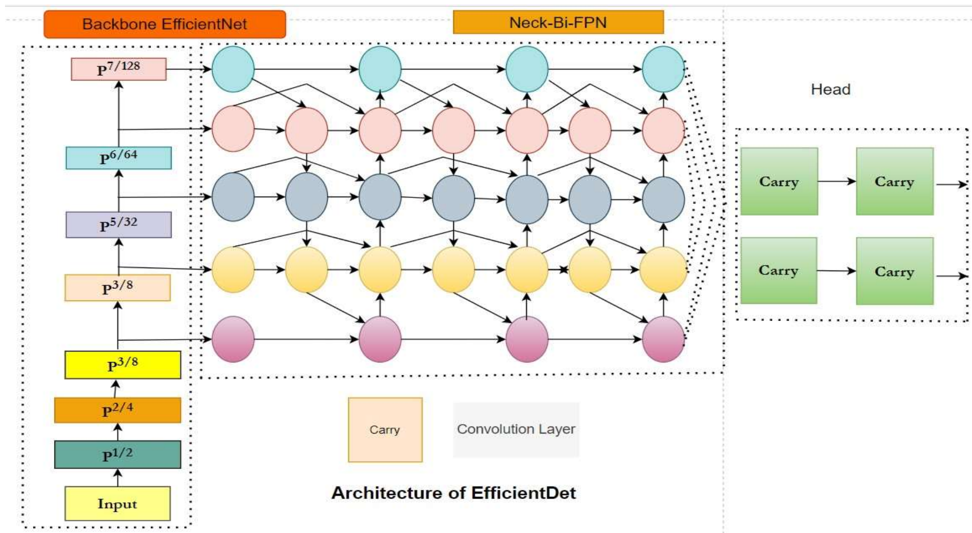

Fig. 6: Architectural structure of EfficientDet.

recognition, perceptron learning seeks to alter weighting. With fewer parameters and FLOPS, Bi-FPN surpasses Yolov50's neck PANet. Feature extraction usually happens through blending pertinent data from a collection of testing and training images, which is called feature fusion. Pixel-level fusion models such as DU, UD-Fusion, RL, and LR-Fusion are used for our proposed work. The objects detected vary with respect to the type of the fusion model, which detects different classes of semantic data. Finally, the compounded scaling strategy involves scaling in terms of precision, depth, width, and resolution of all backbones and feature networks. This is mainly responsible for achieving high performance and accuracy in the case of resource-constrained devices. To perform this, compounded coefficients are utilized. Every component is incremented to a possible range of flexibility in contrast to random increases in parameters. To achieve high precision, more resources are needed (Tan et al. 2020). Fig. 6 provides the architectural structure of EfficientDet.

Classification Using Bi-Directional Gated Recurrent Neural Network

Bi-GRU, being a recurrent neural network, possesses the ability to train the long-term provinces. The disappearing

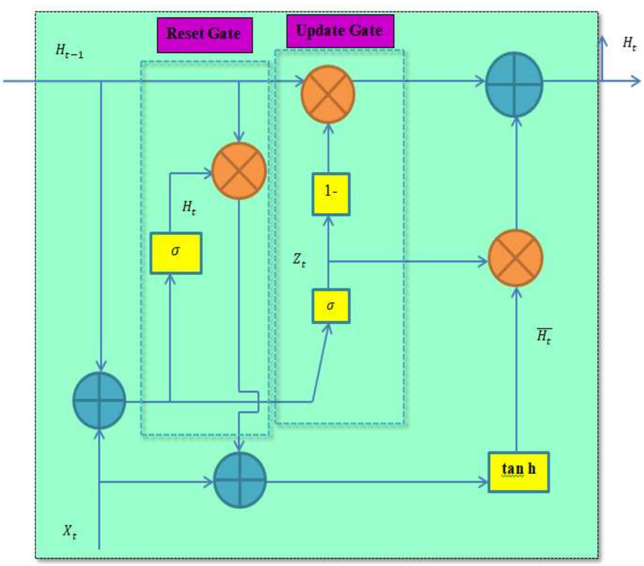

Fig. 7a: Structure of GRU.

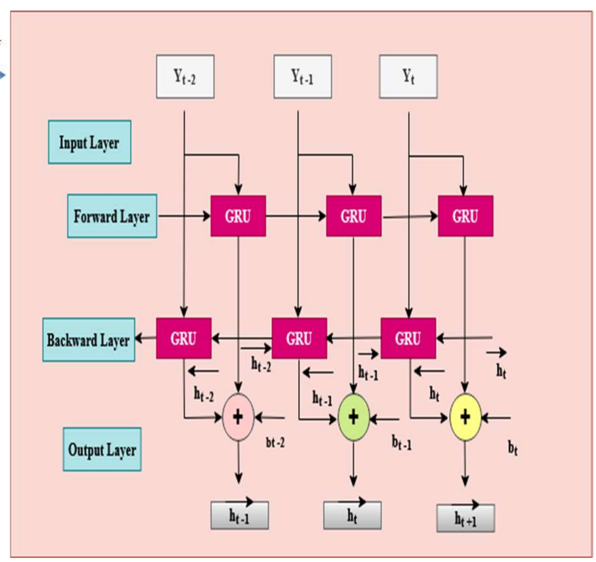

Fig. 7b: Structure of Bi-GRU.

slope problem arising from the derivation of the input signal is fed as input to the construction of the neural net. To overcome this problem, the learning algorithm has to be changed. For instance, in the input layer, Gaussian has to be replaced by ReLu. The slope, which is computed across T time steps, is used to update the connection weights. The conditional variance velocity is equal to the average of T slopes, identical to RNNs. Every one of these T sub-gradients ought to vanish for the standard deviation slope to do so as well. Both training and prediction will make use of the composite features, which include motion, spatial, and deep data. GRU receives the combined feature vector pairs of the detections and predictions, and the output is the feature pair's similarity. In particular, we use GRU networks to encapsulate long-term dependencies in the sequence of data (Lit et al. 2021).

An empirical analysis using a gated recurrent unit, which yields the same performance as that of LSTM, has been chosen in our proposed work (Chung et al. 2014). The simplified version of long short-term memory networks (LSTM) is called Gated Recurrent Units (GRUs). GRU is also a type of the recurrent neural network (RNN). The major difference between LSTM and the GRU is that GRU couples the input and output gate into the update gate. A simple structure of a GRU is depicted using Fig. 7a.The structure of a Bi-directional GRU is depicted in Fig. 7b.

Let us assume that the h is the hidden layer, $X_t \epsilon R^{n*d}$. Where n is the number of samples and d is the number of units, the hidden state at the previous time t-1 is $H_{t-1} \epsilon R^{n*h}$. Σ is the sigmoid activation function. The output hidden state h of a single GRU at the current time step t can be given as follows:

$$R_t = \sigma(X_t W_{rx} + H_{t-1} W_{hr} + b_r) \quad \ldots(1)$$

$$Z_t = \sigma(X_t W_{xz} + H_{t-1} W_{hz} + b_z) \quad \ldots(2)$$

$$\overline{H_t} = tanh\,(X_t W_{xh} + (R_t \odot H_{t-1}) W_{hh} + b_h) \quad \ldots(3)$$

$$H_t = (1 - Z_t) \odot H_{t-1} Z_t \odot \overline{H_t} \quad \ldots(4)$$

$$\sigma(x) = {}^{1}\!/_{1 + e^{-x}} \quad \ldots(5)$$

From the equations (1), (2) and (3) W_{rx}, W_{hr}, W_{xz}, W_{hz} defines the weights of the connecting layers between the input layer and reset gate, hidden layer and reset gate, input layer and update gate, hidden layer and reset gate. Similarly, b_r and b_z define the bias of the reset and update gates. $\overline{H_t}$ is the candidate hidden state of the current time step t, ⊙ represents the multiplication of matrices of two elements, tan h being the hyperbolic activation function, then the formula can be given as:

$$tanh(x) = 1 - {}^{2}\!/_{1 + e^{-2x}} \quad \ldots(6)$$

This indicates that the parameters necessary for the outbreak of forest fires get predicted, the current value is relatively closer to that of the previous time and the value of the next time.

Bi-GRU (Yan et al. 2021) consists of two units of GRUs comprising forward propagating GRU and backward propagating GRU.

$$\vec{H}_t = GRU(X_t, \vec{H}_{t-1}) \quad \ldots(7)$$

$$\overleftarrow{H}_t = GRU(X_t, \vec{H}_{t-1}) \quad \ldots(8)$$

$$H_t = w_t \vec{H}_t + v_t \overleftarrow{H}_t + b_t \quad \ldots(9)$$

From the equations (7), (8), (9) X_t-current input decides the hidden layer state of Bi-GRU, the outputof $\vec{H}_t$ the forward hidden layer and the output $\overleftarrow{H}_t$ of the backward hidden layer at time step t-1, then GRU(.) indicates the GRU network performs the non-linear transformation of the forest fire input image. The input vector is fed into the corresponding GRU hidden state. w_t, v_t -defines the weights of the state $\vec{H}_t$ of the forward hidden layer and $\overleftarrow{H}_t$ of the backward hidden layer at a time t, b_t defines the bias of the state of the hidden layer at time t. With Adam's gradient descent optimization approach, the GRU network is trained to predict similarity using the cross-entropy loss function. In the case of sporadic data, optimization techniques provide an active learning performance. Min-batch learning technique has been applied to the gradient descent method. Two gates are inserted into the GRU-NN to control of flow of information, as shown in the equations from (1)-(9). Since our proposed technique heavily relies on the weights, which can be controlled efficiently by the utilization of optimization technique. Fractional calculus is incorporated along with the Crow Search and Taylor Spotted Hyena optimization (CSFCO).

Solution Encoding

GRU network should be given the optimal weights, which are fed to encode the solution of the CSFCO procedure. Several possible solutions support any length of input or destination. The optimal weights for the Bi-GRU-NN network must be established to encode the CSFCO process solution. The space of potential solutions has [1Z] items. It supports any length as an input or destination. Random input variables are processed by RNN by using its memory space. As a result, RNNs are the best at predicting the actual phrase within a string of sentences. If there are no microorganisms in a GRU level but ni1 in the level before, then each component of the cell will have ni1+ni components.

Fitness Evaluation

The proposed CSFCO technique utilizes the minimization function obtained as the GRU-error NN's function to decide the fitness. The fitness function can be expressed as

$$Z = {}^{1}/_{N} \sum_{n=1}^{N} (O^n - D^n)^2 \quad \ldots(10)$$

Equation (10) O^n defines the GRU-NN's output and D^n defines the expected output. The optimization process, also known as the inference engine, establishes how closely a given resolution conforms to the optimum option toward the desired issue. It determines the suitability of optimizers. The preceding sentence defines the fitness measure for the optimization process. Optimization-derived weights need to provide minimal classification mistakes.

Algorithm for CSFCO Procedure

The proposed work incorporates the swarm intelligence approach to crow search (Askarzadeh et al. 2016) and the fractional calculus technique. The actions of crows, like the intelligence of stealing and hiding food, are mimicked. The mirror test proved that they exhibit self-awareness. Crows provide alerts by recognizing faces in case of an unfriendly one. Even after several months, they remember the place where they hide their food (Corvus 2024, Hooded Crow 2024, Prior et al. 2008, Rincon 2005). In their method, though the first-order derivative solution yields peculiar results for the periodic system, the second-order derivative incorporates previous solutions. This second order-based derivative solution yields either a maxima or minima value. The slope becomes upward if the partial derivative number is a favorable string if the partial derivative number is negligible. Crow search provides faster solutions at the local search in a speedy manner. The attributes utilized for the execution of the crow search algorithm are Nmax, representing the maximum number of iterations; Psize, indicating the size of the population; Pa being the probability of awareness, which provides a trade-off between the exploration and exploitation phase, flen is the flight length and mem being the memory value of the food hiding places of each crow (Crepinsek 2013). The crows operate in the exploration and exploitation phase, which can be described as follows:

Step 1: Population Initialization

The number of crows in the current CSO is chosen as random. Let us assume that there are n possible solutions where the space of solutions can be defined as

$$Cr = \{Cr_1, Cr_2, Cr_3, \ldots., Cr_n\} \,\forall 1 \leq i \leq N \quad \ldots(11)$$

Where Cr_i defines the ith solution in the answer space.

Step 2: Fitness Evaluation and position update: To find the optimal weights for the GRU network, it is used for optimization.

Case 1: When a single crow finds food, the population gets updated, which can be defined by the equation (12)

$$Cr_{new,i} = rand, \forall\, 0 \leq rand \leq 1 \quad \ldots(12)$$

Equation (12) shows that the crow is followed.

Case 2: When a crow does not know that it is being followed. The population gets updated, which can be defined by equation (13) as follows:

$$Cr_{new,i} = Cr_i + rand * flen * (mem_i - Cr_i)\; Iff\; rand > pa \quad \ldots(13)$$

The position update of the

$$Cr_{i,j}(t+1)) = Cr_{i,j}(t) + v_i(t) + rand * flen * \left(mem_{i_{best}} - Cr_{i,j}\right) \quad \ldots(14)$$

Rearranging the equation (14)

$$Cr_{i,j}(t+1)) - Cr_{i,j}(t) = v_i(t) + rand * flen * \left(mem_{i_{best}} - Cr_{i,j}\right) \quad \ldots(15)$$

Step 3: Using fractional calculus, the second-order derivative can be given as

$$D^n\left(Cr_{i,j}(t+1)) - Cr_{i,j}(t)\right) = v_i(t) + rand * flen * \left(mem_{i_{best}} - Cr_{i,j}\right) \quad \ldots(16)$$

To solve equation (16) by taking the second-order derivative, we have

$$Cr_{i,j}(t+1)) - \alpha Cr_{i,j}(t) - \frac{1}{2}\alpha Cr_{i,j}(t-2)) - \frac{1}{6}\alpha(1-\alpha)(Cr_{i,j}(t-2)) - \frac{1}{24}\alpha(1-\alpha)(2-\alpha)Cr_{i,j}(t-3)) = v_i(t) + rand * flen * \left(mem_{i_{best}} - Cr_{i,j}\right) \quad \ldots(17)$$

From equation (17), the full appearance of the position update can be defined by equation (18)

$$Cr_{i,j}(t+1)) = \alpha Cr_{i,j}(t) - \frac{1}{2}\alpha Cr_{i,j}(t-2)) - \frac{1}{6}\alpha(1-\alpha) Cr_{i,j}(t-2)) - \frac{1}{24}\alpha(1-\alpha)(2-\alpha)Cr_{i,j}(t-3)) = v_i(t) + rand * flen * \left(mem_{i_{best}} - Cr_{i,j}\right) \quad \ldots(17)$$

Step 4: After the best optimal value is found, it will be swapped from best to j, which will be the perfect fitness value.

Step 5: When the ideal weight gets obtained, it will be fed as input to the GRU

RESULTS AND DISCUSSION

The proposed work aims to identify and classify the outbreak of fire by fire alerts using the Crow search fractional calculus optimization technique. Identification of smoke, for in a

Table 3: Comparison of TPR on various techniques with respect to different datasets.

Technique	Bow Fire Dataset	FD-Dataset	Forestry Images	VisiFire Dataset
FL	94.70%	94.00%	90.50%	91.30%
EE-DCNN	93.80%	91.70%	92.50%	93.50%
LWDL	90.40%	89.80%	93.70%	95.80%
DBN-RLSTM-NN	89%	92.60%	95.60%	95.30%
CSO-RLSTM-NN	98.60%	96.80%	97.40%	96.60%
CS-Bi-GRU-NN	97.89%	97.20%	97.60%	97.80%

Table 4: Comparison of FPR on various techniques with respect to different datasets.

Technique	BowFire Dataset	FD-Dataset	Forestry Images	VisiFire Dataset
FL	3.90%	3.60%	4.20%	5.90%
EE-DCNN	4.20%	4.10%	3.70%	5.30%
LWDL	5.60%	5.30%	3.10%	4.80%
DBN-RLSTM-NN	7%	4.50%	2.50%	4.30%
CSO-RLSTM-NN	1.40%	2.50%	1.30%	3.60%
CS-Bi-GRU-NN	1.30%	2.30%	1.20%	3.40%

hostile environment happens using IoT devices. IoT devices once deployed, sense, capture, and transmit the captured information for further processing. Huge data will be obtained which will be of the data set, out of which 70% has been utilized for training and 30% for testing.

Performance Metrics

The proposed work has been evaluated by utilizing performance metrics, namely True Positive Rate (TPR), False Positive Rate (FPR), Error_Rate, and Accuracy. These metrics facilitate efficient prediction before the Outbreak of fire – The formula to calculate the performance metric is as follows:

$$TPR = {True\ Positive}/{False\ negative\ +\ True\ Positive} \quad \ldots(18)$$

$$FPR = {False\ Positive}/{True\ Negative\ +\ False\ Positive} \quad \ldots(19)$$

$$Precision = {True\ Positive}/{True\ Positive + \ False\ Positive} \quad \ldots(20)$$

$$Error\_Rate = {False\ Positive + False\ Negative}/{False\ Negative} \quad \ldots(21)$$

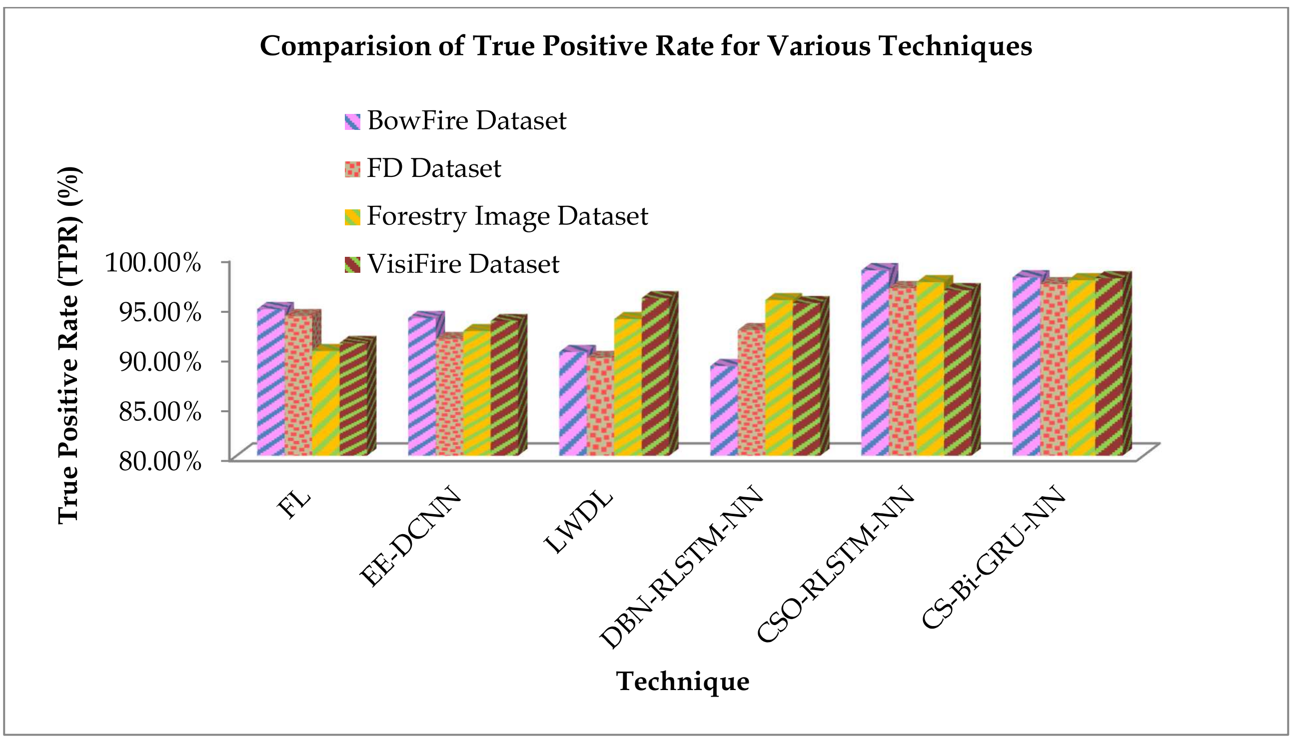

Fig. 8: Comparison graph of TPR for various techniques on different datasets.

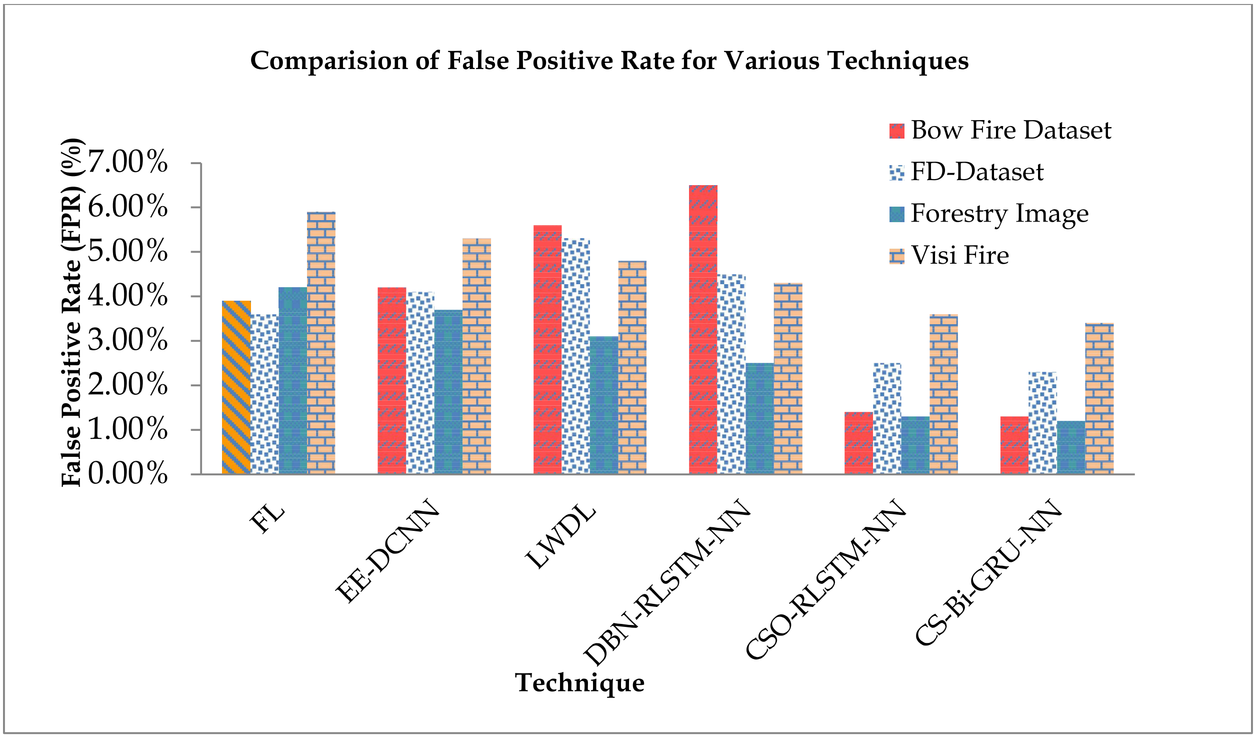

Fig. 9: Comparison graph of FPR for various techniques on different datasets.

Table 5: Comparison of Accuracy of various techniques with respect to different datasets.

Accuracy (%)				
Technique	Bow Fire Dataset	FD-Dataset	Forestry Images	VisiFire Dataset
FL	95.2%	94.2%	90.1%	91.2%
EE-DCNN	94.1%	91.5%	92.4%	93.2%
LWDL	91.2%	89.6%	93.6%	94.6%
DBN-RLSTM-NN	89.4%	92.3%	95.3%	95.2%
CSO-RLSTM-NN	98.4%	96.4%	97.3%	96.7%
CS-Bi-GRU-NN	98.9%	97.5%	97.6%	97.4%

Table 6: Comparison of error rate on various techniques with respect to different datasets.

Technique	Bow Fire Dataset	FD-Dataset	Forestry Images	VisiFire Dataset
FL	0.38	0.35	0.43	0.61
EE-DCNN	0.42	0.43	0.38	0.52
LWDL	0.63	0.53	0.31	0.46
DBN-RLSTM-NN	0.75	0.42	0.25	0.42
CSO-RLSTM-NN	0.14	0.26	0.13	0.37
CS-Bi-GRU-NN	0.12	0.23	0.1	0.35

Comparative Analysis based on True Positive Rate (TPR)

Table 3 provides the experimental analysis of the TPR of the proposed work compared with the existing technique with respect to different datasets. Fig. 8 provides the comparison graph on TPR of the proposed work compared with the existing technique with respect to different datasets.

Comparative Analysis Based on False Positive Rate (FPR)

Table 4 provides the experimental analysis of the FPR of the proposed work compared with the existing technique with respect to different datasets. Fig. 9 provides the comparison graph on the FPR of the proposed work compared with the existing technique with respect to different datasets.

Comparative Analysis Based on Accuracy

Table 5 provides the experimental analysis of the accuracy of the proposed work compared with the existing technique with respect to different datasets. Fig. 10 provides the comparison graph on the accuracy of the proposed work compared with the existing technique with respect to different datasets.

Comparative Analysis based on Error_Rate

Table 6 provides the experimental analysis of the error rate

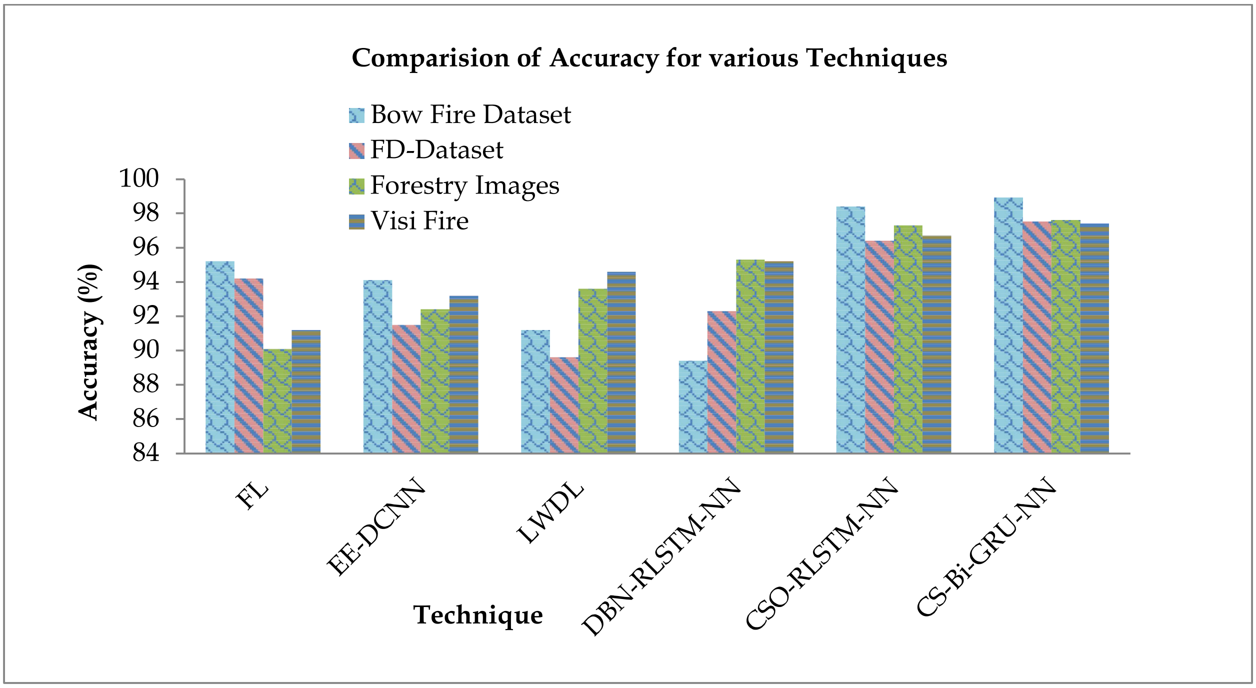

Fig. 10: Comparison graph of accuracy for various techniques on different datasets.

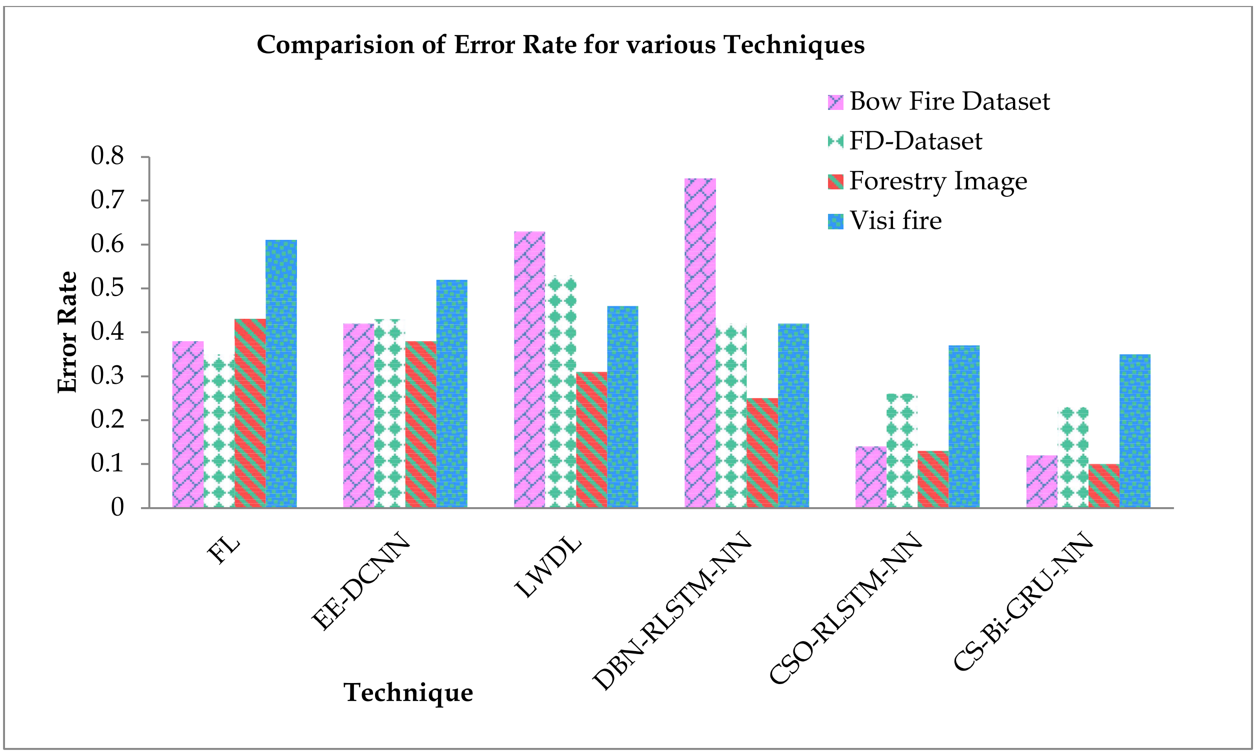

Fig. 11: Comparison graph of error rate for various techniques on different datasets.

of the proposed work compared with the existing technique with respect to different datasets. Fig. 11 provides the comparison graph on the error rate of the proposed work compared with the existing technique with respect to different datasets.

CONCLUSIONS

Our proposed work has been based on a forest fire detection system by coagulating Crow Search with a Bi-GRU-NN model. Forest fires can be detected efficiently by object detection models. To assist this, CNN performs efficiently. Nevertheless, it is difficult for an individual object detection to detect forest fires in a hostile environment like forests. Additionally, object detectors cannot be able to distinguish between chimney smoke and clouds. This induces the fake positive rate owing to the narrow range of object detectors. Since our proposed work utilized a Crow search-based optimization algorithm, it exhibits high efficiency.

Further work can be extended by the use of LSTM & its variants for other emergency scenarios. In addition, to prevent unwanted false negatives, smoke detection models have to be built. Different optimization techniques can be adopted to assess the comparative performance for efficient use in forest fire detection.

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