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Research article

Enhancing safety for blind and visually impaired people: intelligent fire detection using deep learning and the lemurs optimization algorithm

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Abstract: An increased number of older people suffer from higher levels of cognitive and vision impairments, which usually results in loss of independence. Fire detection systems play a crucial role in providing timely alerts to blind and visually impaired (BVI) individuals during indoor emergencies. As fire detection is complex and critical for safety, deep learning (DL) has recently been adopted for precise recognition. Efficient algorithms are crucial for hardware-constrained devices like embedded systems, robots, and mobiles to ensure high performance with low power use. In this paper, an enhanced fire detection system for blind and visually challenged people using artificial intelligence (AI) and Lemurs Optimisation Algorithm (EFDBVCP-AILOA) model is proposed. The aim is to assist visually impaired individuals by using DL techniques. Primarily, the adaptive bilateral filtering (ABF) method is used to reduce noise while preserving essential edges in fire images. For feature extraction, the NASNetMobile method is employed to capture complex features from the image data. Furthermore, the EFDBVCP-AILOA method implements self-attention with a convolutional neural network and long short-term memory (CNN-Sa-LSTM) model for classification. Finally, the Lemur's Optimisation (LO) model is employed as a parameter-tuning approach for the CNN-Sa-LSTM model. A wide-ranging experimentation of the EFDBVCP-AILOA approach is accomplished under the fire detection dataset. The comparative results of the EFDBVCP-AILOA approach demonstrated superior $accu_y$ of 97.07%, with $prec_n$, $reca_l$, and

$F_{measure}$ values of 96.98%, 97.07%, and 97.00%, respectively. The EFDBVCP-AILOA approach applied four performance metrics to evaluate and compared done with seven recent models.

Keywords: fire detection; lemurs optimization; image pre-processing; visually challenged people; artificial intelligence
Mathematics Subject Classification: 37M10

1. Introduction

Human population is quickly increasing in the world and again leading to a growing number of BVI people [1]. BVI, as well as ageing people, face several difficulties while performing routine activities that include work, housekeeping, sports practice, travelling, and environmental awareness, due to sensory, cognitive, and physical decline [2]. This situation is critical, considering that number of people with vision difficulties is increasing significantly, especially in emerging nations, as developments in medical care systems enable a longer life expectancy. Many solutions have become advanced for these problems, and assistive and software technologies have been proposed to aid BVI persons [3]. Utilizing an early notification and fire-recognition arrangement for BVI individuals could reduce property loss, patient counts, and, importantly, early deaths. Electrical distribution, heating and lighting equipment, cooking, specific smoking materials, and fire initiation are the five reasons that play a significant role in inside fires and fatal fires [4]. BVI people have the highest risk of death and injury due to fire threats. Based on the seriousness of their visual impairment, a fire can start by accident during routine housework, making it less possible to avoid or solve it [5].

Moreover, BVI people are highly vulnerable to sustaining burns after trying to control very few fires. Some related research on outdoor fire detection has been put forward in the last decade. Still, there is a lack of analysis on initial notification systems and fire detection for BVI individuals utilizing AI methods in indoor settings [6]. Instead of fire safety applications, assistive technology has been proposed to offer quick safety information and fire prevention to BVI individuals rapidly during outdoor and indoor fire emergencies [7]. Still, these technologies suffer from some limitations. They trigger false alarms having a high rate of false detection compared with vision- based systems and DL. Such limitations are concerning given the large percentage of visually impaired people and the significant population living in developing nations [8]. To prevent fires from spreading, it is essential to detect them quickly minimizing unnecessary alerts and false alarms. BVI people may use a combination of DL, computer vision (CV), and smart glasses [9]. Additionally, the predictable indoor fire-detection structure is relevant to various industrial and social domains, such as offices, chemical plants, schools, hospitals and factories. Several publications have focused on wildfire and outdoor environments for fire detection, with a lack of research on indoor environments [10].

1.1. Motivation for intelligent fire detection systems for visually impaired individuals

As the global populace quickly ages, the number of visually impaired individuals is on the rise, posing crucial threats to daily safety and independence. These individuals face hazards such as accidental fires and accidents in household activities due to restricted sensory awareness. Thus, it is crucial to try to prevent severe injuries and loss of life through early fire detection. Developing intelligent, accessible detection systems can significantly improve the safety of these individuals by providing timely alerts and reducing emergency response times. Furthermore, many existing fire detection solutions are not constructed to the specific requirements of visually impaired users, which limits their effectiveness. There is a crucial requirement for affordable, real-time systems that can operate reliably in diverse home environments. Addressing these challenges can significantly improve the quality of life and safety for visually impaired individuals worldwide.

1.2. Key contributions and novelty of the EFDBVCP-AILOA technique

This paper proposes an enhanced fire detection system for blind and visually challenged people using the artificial intelligence (AI) and the Lemurs Optimisation Algorithm (EFDBVCP-AILOA) model. The aim is to assist visually impaired individuals by using DL techniques. The most significant contributions of the EFDBVCP-AILOA method are listed below:

The EFDBVCP-AILOA model utilizes the ABF approach for image pre-processing and employs the NASNetMobile architecture for extracting complex features. Furthermore, the system uses a CNN-Sa-LSTM model for classification and optimizes performance with the LO technique.

The EFDBVCP-AILOA technique integrates ABF-based pre-processing to improve the quality of the image, improving fire detection accuracy. This method effectively mitigates noise while conserving significant image features. Refining the input data enables more reliable fire detection, particularly for visually impaired individuals.

The NASNetMobile architecture is utilized to capture intrinsic features from image data, enabling effective and precise fire detection. This lightweight architecture is appropriate for real-time processing, making it ideal for deployment in resource-constrained environments. It improves the model's capability to detect key fire-related features in diverse scenarios.

The EFDBVCP-AILOA method incorporates a CNN-Sa-LSTM model to improve classification accuracy. This integration allows the technique to concentrate on crucial features while retaining temporal dependencies for more accurate fire detection. As a result, it enhances overall system performance, specifically in dynamic environments.

The integration of an LO model for tuning the fire detection system depicts a novel methodology that improves both performance and efficiency. This optimization technique fine-tunes the parameters of the system to attain improved detection accuracy and faster processing. By intelligently adjusting the settings of the model, it confirms optimal performance in real-world scenarios, setting it apart from conventional methods.

The structure of the article is organized as follows: Section 2 provides a review of the literature, Section 3 describes the proposed method, Section 4 presents the evaluation of results, and Section 5 offers the study's conclusions.

2. Literature survey

AI solutions for visually impaired individuals have advanced significantly, presenting innovative tools to improve safety and independence. Recent developments include smart canes with sensor systems and real-time assistive devices using DL and CV for fall detection and object/face recognition. These technologies aim to provide reliable, affordable, and practical support in diverse environments. These advancements empower visually impaired users to navigate daily challenges with greater confidence and autonomy. In particular, AI-based fire detection systems offer a critical layer of safety by enabling timely alerts and rapid response in hazardous situations. In [11], a TENG-based smart cane and associated sensor system using a user-friendly framework and very minimal cost was developed to help the visually impaired people. The presented smart cane depends on a single-electrode-mode TENG connected to the lowest part of the cane to identify possible risks. The electric outputs among the lowest friction layers and general road materials were consistently examined, and the most suitable identifying components were designated. Additionally, a four-wall square cage framework and associated wireless sensor system was developed for falling-down recognition. The as-designed system can gather falling-down signals and transfer them over Bluetooth. In addition, the presented smart cane can attain longer-range durability and functions in water-spraying situations, which displays potential applicability in a water-based environment. Kamal et al. [12] discussed the importance of developing a real-time system with a Raspberry Pi for processing data points presented through ultrasonic sensors and a camera using a simpler feedback method to notify the user over a headset. The recommended method works in several situations, either inside or outside the environment, and has numerous operation modes to assist the BVI in various conditions; it has minimal hardware for reasonable devices with an acceptable offline real-time performance. This method mainly uses DL technologies using CV technique to professionally solve general problems, namely face recognition, object recognition, and text reading.

In [13], a new, simple, robust, handy, and cost-efficient solution was presented using smartphone assistance. Objects are captured using a camera, segmented using the Hybrid Canny Edge Detector and Hough Transform-based Algorithm (HCED–HT) technique, and detected by the strong improved momentum search (IMS)-based YOLO-v7 model. Once identified, the following stage is to estimate the distance between the VIPs and the object and communicate with them using the audio devices or headphones. Said et al. [14] proposed an intelligent navigation-aided system for visually impaired individuals. The DL methods have made significant progress toward a well-planned structure. Also, neural architecture search (NAS) is a promising technique for automatically searching for optimal architecture and reducing the need for manual design. A quick NAS was presented to search for object detection structures to evaluate its effectiveness. In exploring feature pyramid networks and the prediction phase for an anchor-free object detection method. The proposed NAS relies on a tailored reinforcement learning method. Kumar et al. [15] developed a new method that incorporates Google Speech input and text-to-speech technologies. This new method enables users to perform various tasks, such as detecting weather conditions, reading, using simple voice commands, and finding locations. This straightforward application has significantly increased social interaction and day-to-day work for visually impaired people, underlining the crucial role of accessibility in technological advancements. Kuriakose et al. [16] introduced DeepNAVI, a smartphone-based navigation helper that utilizes DL. Besides identifying obstacles, the method also provides information regarding their location, motion status, scene information, and distance from the user. All information is presented to users in audio mode without compromising convenience and compactness. With its smaller size and fast inference time, the system works efficiently on smartphones in real-time. Yunusov et al. [17] presented a forest fire detection technique using Transfer Learning (TL) with the YOLO-v8 relating method and the TranSDet approach, which incorporates an enhanced DL model. The TL-based on pre-trained YOLO-v8 approach enables fast and precise object detection while the TranSDet architecture to identifies smaller fires.

Al-Wesabi, Alharbi, and Yaseen [18] proposed the smart fire detection system for assisting the blind using attention mechanism-driven recurrent neural network and Seahorse Optimiser Algorithm (SFDAB-ARNNSHO) technique, which utilizes Sobel filtering (SF) to eliminate noise from input images efficiently. The feature extraction process incorporates three powerful techniques, namely EfficientNetB7, Capsule Network (CapsNet), and ShuffleNetV2, for capturing robust and diverse features for accurate fire detection and classification. Chitram, Kumar, and Thenmalar [19] aimed to review the advancements in real-time fire and smoke detection using DL and image-processing techniques. Buriboev, Abduvaitov, and Jeon [20] developed a Convolutional Neural Network (CNN) model by incorporating hybrid pre-processing techniques, comprising contour-based algorithms and colour feature analysis. Buriboev et al. [21] proposed a novel fire detection method by integrating contour analysis with a deep CNN. Sujatha et al. [22] presented a fire detection system using Internet of Things (IoT) and vision sensors by integrating a Residual Channel Attention Network (RCAN) with a Deep Dilated CNN (DDCNN) methodology. The model is optimized using the Crayfish Optimisation Algorithm (COA) to enhance accuracy and response time. Said et al. [23] evaluated low-cost, real-time fire detection systems using standard ML models comprising Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Multinomial Naive Bayes (MNB), Gradient Boosting (GB), K-Nearest Neighbours (kNN), Multi-Layer Perceptron (MLP), and the DL model Visual Geometry Group 16 (VGG16). Lee et al. [24] proposed an integrated fire safety system by integrating edge AI, hybrid sensors, and precision suppression techniques to achieve fast, accurate fire detection and efficient flame control. Wang et al. [25] presented a fire recognition model based on the Convolutional Block Attention Module with EfficientNetV2 (CBAM-EfficientNetV2) technique to improve accuracy and small target detection in fire images. Khan et al. [26] introduced a system that uses a fusion of static and dynamic features with a CNN and long short-term memory (CNN-LSTM) model. Jahan et al. [27] introduced an IoT-based firefighting drone integrating real-time fire detection, gas concentration monitoring, and adaptive fuzzy-based backstepping control for precise navigation and fire suppression. The model also utilizes the Pixhawk PX4 microcontroller and telemetry system.

2.1. Overview of recent advances in AI for visual impairment assistance

The utilization of AI and DL models highlights significant advancements in improving assistive technologies for VIPs. The innovations range from smart canes with integrated sensors and wireless communication to smartphone-based navigation aids using object detection and speech interfaces. Techniques, namely NAS and TL, have enhanced model efficiency and accuracy, enabling more effective obstacle detection and environment comprehension. However, while these advancements exhibit promise, many solutions remain in controlled settings, emphasizing the requirement for more robust, real-world applications built to address user-specific threats. Additionally, the integration of multimodal data, comprising audio, vision, and tactile feedback, is gaining attention to create more intuitive and comprehensive assistance systems. Continuous efforts concentrate on optimizing models for mobile and embedded platforms to ensure accessibility and real-time responsiveness for VIP users.

2.2. Limitations and research gap in AI-based assistive systems for VIPs

The existing outcomes present various threats, such as restricted real-time performance on low-power devices, insufficient robustness in diverse environments, and a lack of comprehensive integration of multi-sensor data. Various models depend on expensive or bulky hardware, limiting widespread utilization. Furthermore, few studies thoroughly address false alarm reduction or user-centric evaluations specific to VIP requirements. The research gap is in developing lightweight, cost-effective, and highly reliable systems that balance accuracy, latency, and usability for practical, everyday use by VIPs. Additionally, the consistency and efficiency of various studies are affected by limitations in adaptability to dynamic real-world scenarios. There is also a scarcity of standardized benchmarks and datasets specifically built for VIP applications, limiting fair comparisons across methods. Addressing these gaps is crucial to advance assistive technology that meets the diverse needs of VIP users.

3. Proposed methodology

In this paper, an EFDBVCP-AILOA methodology is presented. The EFDBVCP-AILOA technique focuses on an advanced fire detection system to assist visually impaired individuals by leveraging DL techniques. To accomplish this, the EFDBVCP-AILOA approach comprises four distinct step-by-step processes: initially, ABF-based image pre-processing; next, the NASNetMobile feature extractor; followed by hybrid classification models; and finally, LO algorithm-based parameter tuning, as depicted in Figure 1.

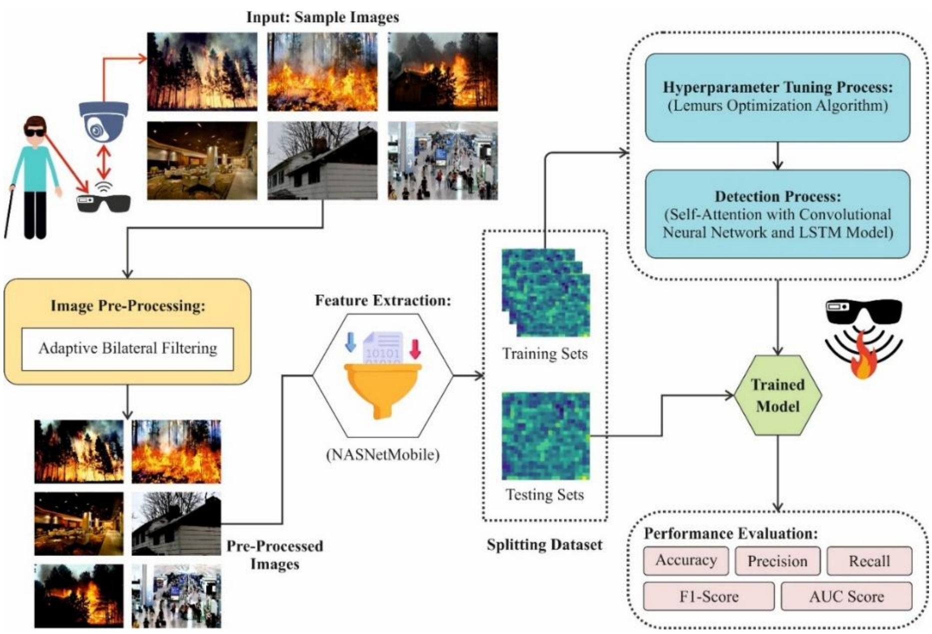

Figure 1. Overall process of EFDBVCP-AILOA method.

3.1. Image pre-processing: ABF model

The EFDBVCP-AILOA technique conducts image preprocessing using ABF to reduce noise while preserving essential edges in fire images [28]. This model was chosen due to its ability to maintain edges while efficiently mitigating noise in images, making it ideal for enhancing the quality of input data. Unlike conventional filters, ABF adapts to the local content of the image, providing an improved preservation of essential features while smoothing irrelevant noise. This characteristic makes ABF especially useful for tasks requiring high accuracy in recognizing subtle patterns, such as gesture recognition or activity detection. Its capability to maintain fine details while filtering out unwanted discrepancies provides a clear advantage over other filtering methods in scenarios with complex or noisy data. ABF is a great image-preprocessing model used in fire detection systems intended to help BVI people. By successfully decreasing noise while preserving important details and edges, ABF improves the features of fire-related images, guaranteeing richer feature extraction. This model fine-tunes the filtering method depending on local image features, facilitating the differentiation between non-fire components in several lighting situations. As a result, it increases the accuracy of successful classification tasks by DL methods. Generally, ABF plays a critical part in improving the reliability of fire detection systems intended for visually impaired users.

3.2. Feature extraction: NASNetMobile

For the process of feature extraction, the NASNetMobile architecture was employed as a lightweight yet powerful model that efficiently captures critical features from complex image data [29]. This method is chosen due to its effective architecture, offering a good balance between performance and computational cost. As a lightweight model, it is appropriate for real-time applications on resource-constrained devices, such as mobile or embedded systems. NASNetMobile has been optimized for high accuracy in image classification tasks, making it ideal for capturing intrinsic features in various environments. Compared to other models, it gives state-of-the-art performance with fewer computational resources, making it more accessible for practical deployment. Its scalability confirms robustness while maintaining efficiency, making it an excellent choice for feature extraction in real-world applications.

NASNetMobile, a structure CNN-type was established by Google. It was specially intended for effective mobile applications and is a part of Google's NAS plan. Using a neural structure search method, NASNetMobile independently projects a CNN structure enhanced for mobile devices. This framework includes numerous convolutional layers with different filter sizes, accompanied by max-pooling layers to downsample the feature maps. Furthermore, it includes skip connections to increase the information flow among layers and lessen the gradient vanishing problem. Even though it has computational competence, NASNetMobile attains higher precision, making it appropriate for utilization on devices with restricted resources like embedded and smartphone systems. Additionally, NASNetMobile is pre-trained on wide-ranging image datasets, namely ImageNet, permitting it to learn composite visual features efficiently.

In the framework of NASNetMobile, cell architecture plays an essential part. These architectures include two different kinds: reduction cells and normal cells. Containing numerous convolutional layers with combinable and reusable features, these cell architectures create sub-networks. NASNetMobile builds its complete network by assembling these essential components (reduction and normal cells). This modular method gives NASNetMobile considerable flexibility, allowing it to adjust different task requests and source limits.

3.3. Classification: hybrid CNN-Sa-LSTM

Furthermore, the EFDBVCP-AILOA technique applies the CNN-Sa-LSTM model [30]. This approach was chosen due to its ability to capture spatial and temporal dependencies in data effectively. The CNN extracts spatial features from the input, while the self-attention mechanism improves the model's focus on relevant parts of the data. The LSTM component allows for the modelling of long-range temporal dependencies, significant for dynamic and sequential data. This incorporation enables the model to recognize intrinsic patterns and context in time-series data. Compared to other models, this hybrid approach gives superior accuracy and robustness, specifically in applications like activity recognition and gesture classification. From both the streams of CNN, the extracted features with attention mechanisms (motion and spatial) are linked. Spatial CNN is based on static appearance data, while motion CNN captures temporal changes between frames. Concatenating these features allows the method to inspect spatial and temporal data simultaneously, which improves the performance. By uniting the features throughout additional handling, the technique absorbs connection motion and spatial signals, which leads to many dense models and enhanced performance in tasks like action identification. These concatenated feature models served in advanced phases of a system for further classification or study. Figure 2 depicts the framework of CNN-Sa-LSTM.

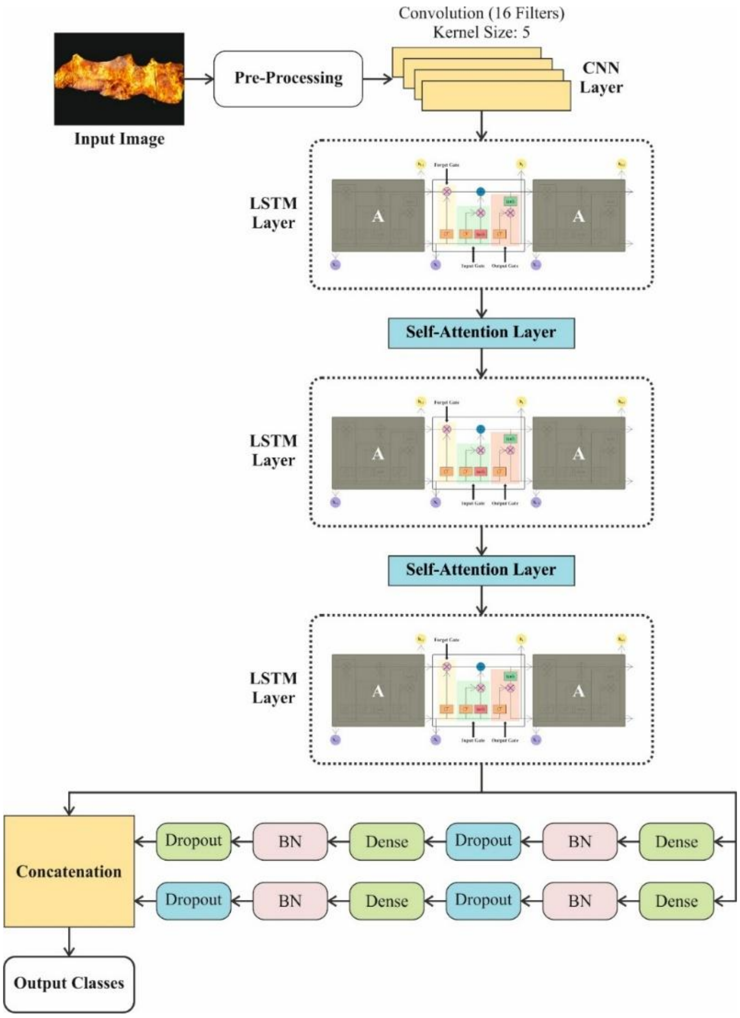

Figure 2. Framework of CNN-Sa-LSTM method.

➢ **CNN**

CNN is employed to extract spatial features from input data such as video or picture frames. It contains many layers, such as pooling, convolutional, and fully connected (FC). Convolutional layers employ filters on an input to discover patterns, while the pooling layer reduces the dimensionality while preserving vital features. CNNs might remove frame-level features in the analysis of video, taking spatial data in every structure.

➢ **LSTM**

The internal memory cell and gates, such as output, forget, and input, are employed at every stage. The forgetting gate equates the preceding condition of the cell of the current input to define which data to keep across the history. The input gate chooses which novel data is significant for taking the sign. The output gates define which data from the current cell state is beneficial for the present output and upcoming predictions. The LSTM model acquires time-based relationships among the signs by assessing the collective features gradually and using the memory cell and gates. The mathematical formulation employed for the LSTM method is given below:

- Forget gate: This gate controls an amount of data, which is eliminated from the previous cell state as exposed in Eq (5)

$$g_r = \sigma\left(V_g.[F_{r-1}, Y_r] + a_g\right). \tag{1}$$

- The input gate decides how much new information is kept in the cell state, as assumed in Eq (2)

$$j_r = \sigma\left(V_j.[F_{r-1}, Y_r] + a_j\right). \tag{2}$$

- The quantity of the present cell state, is controlled as stated in Eq (3)

$$o_r = \sigma(V_o.[F_{r-1}, Y_r] + a_o). \tag{3}$$

- New data is inserted into the cell state as tackled in Eqs (4)–(6)

$$\widetilde{D}_r = \tan g(V_d.[F_{r-1}, Y_r] + a_d). \tag{4}$$

$$D_r = g_r.D_{r-1} + j_r.\widetilde{D}_r. \tag{5}$$

$$F_r = o_r.\tan g(D_r). \tag{6}$$

Here, and σ signify element-by-element multiplication and the activation function of the sigmoid, respectively. F_{r-1} denotes the preceding hidden layer (HL), D_{r-1} refers to the preceding cell state, g_r denotes the forget gate, j_r means an input gate, 0_r denotes the output gate, and F_r is the upgraded HL. Throughout this procedure, the LSTM network utilizes its capability to manage sequential input for learning time-based patterns amongst the united features, resulting in a well-perceptive model.

➢ **Self-attention**

The self-attention enhances the performance of models by evaluating the significance of numerous parts of an input series. This mechanism allows the method to concentrate on appropriate features and structure actively, changing its focus as per the background. This helps in gathering complex interactions and relationships in the information, which results in more precise detection. For instance, if a person performs an act in a video, the mechanism of self-attention can help the concentration models focus on a specific frame once the act is noticeable, improving complete detection accuracy as demonstrated in Eq (7)

$$X_q = 1/D\left(Y_q\right) \sum_p u\left(Y_q, Y_p\right) g\left(Y_p\right). \tag{7}$$

The input is represented as Y, the united contribution of an input signal is denoted by p, and the function of the softmax output is represented by x. The reply is noted at point q, and every position at a similar signal with dissimilar weights is exhibited at position p.

3.4. Parameter tuning: LO approach

Finally, the LO model is utilized as a parameter-tuning approach for the CNN-Sa-LSTM technique [31]. This technique is chosen for parameter tuning due to its capacity to efficiently navigate large and complex search spaces to find optimal hyperparameters. This methodology integrates exploration and exploitation to avoid local minima, confirming better global optimization. Compared to other optimization models, LO gives faster convergence and improved accuracy in fine-tuning model parameters, enhancing overall performance. Its flexibility and ability to handle multi-dimensional optimization problems make it highly effective for optimizing DL models, confirming that the system attains optimal outputs. Furthermore, LO is computationally efficient, making it appropriate for large-scale applications with limited resources. LO is recognized as a great population-based technique; the set of lemurs is stated in the form of a matrix. Equation (8) describes the matrix of an input population

$$X = \begin{bmatrix} l_1^1 & l_1^2 & . & l_1^d \\ l_2^1 & l_2^2 & . & l_2^d \\ \vdots & \vdots & \vdots & \vdots \\ l_n^1 & l_n^2 & . & l_n^d \end{bmatrix}. \tag{8}$$

Here, X specifies the matrix of the method set in dimension $n \times d$. n denotes the solution of the candidate, and d signifies the decision variable. To utilize the LO for solving an optimizer issue, the LO method runs into numerous steps, which are as follows:

Step 1: Describe the parameters of lemurs, in a N population, Max_{iter} denotes the maximum number of iterations, and d is a dimension of the searching space. Also, LB and UB refer to lower and upper limits, respectively.

Step 2: Produce the decision variable of X in the ith solution depending upon Eq (9):

$$X_i^j = \left(LB + \left(UB_j - LB_j\right)\right) \times r. \tag{9}$$

Here, r denotes the uniform randomly generated number $\in [O, 1]$.

Step 3: In the circle for every iteration, compute $Free\ \ Risl <$ Rate (FRR), which is the constant depending upon Eq (10):

$$FRR = HRR - t \times \left(\frac{(HRR-LRR)}{\text{Max}_{iter}}\right). \tag{10}$$

While t denotes the current iteration's count. Max_{iter} denotes the maximum iteration size.

Moreover, Eq (10) employs high-risk rate (HRR) and low-risk rate (LRR) as dual continuous and pre-defined values.

Step 4: Calculate the value of fitness for every χj_i that is stated in Eq (11):

$$Fit\left(x_i^i\right) = \alpha \times (1 - Acc) + \beta \times \left(\frac{s}{S}\right). \quad (11)$$

In this equation, the fitness value is denoted by $Fit\left(x_i^j\right)$, s represents the total of nominated features, S denotes the highest preferred feature, and Acc refers to the accuracy of every subset to assess the part-subset in every iteration.

Step 5: To increase the fitness value, dual dissimilar procedures are classified. Initially, the best near lemurs (bnl) choose the solution by the final value of fitness. Depending on the FS objective, bnl gives the finest feature for the present iteration. Next, the global best lemur (gbl) is designated from the complete population, which signifies the overall finest solution.

Step 6: Set r_1, which is a randomly generated number $\in [0,1]$, and equate it using FRR. Next, upgrade the location for every lemur far away from the $risl$ <-based on Eq (12)

$$X_i^j = \begin{cases} x(i,j) + |(x(i,j) - x(bnl,j)| \times (r_3 - 0.5) \times 2;\ r_1 < FRR \\ x(i,j) + |(x(i,j) - x(gbl,j)| \times (r_3 - 0.5) \times 2;\ r_1 > FRR \end{cases}. \quad (12)$$

Here, r_1 denotes a randomly produced number $\in [0,1]$. The present ith lemur of the N^{rh} population is denoted by $x(i,j)$, that is, the candidate solution in j^{rh} decision variables. bnl and gbl refer to best and global best lemurs, respectively.

Algorithm 1: Pseudocode of the LO model

Define the parameters such as UB, LB, Max_{iter}, Dimension $d, LRR, and\ HRR$.
Set the dimension of the Lemur population N.
Make population at random by Eq (9)
$t = 1$
while $t < \text{Max}_{iter}$ do
Compute coefficient FRR by Eq (10)
Compute Fir for every candidate Lemurs
Category lemurs' candidates
Upgrade the global best candidate lemur gbl
Upgrade bnl
for $i = 1$ to N do
Initialize $r_1 \leftarrow rcmd[0,1]$
if $r_1 < FRR$ then
Upgrade every decision variable utilizing $dancehup$ in Eq (12)
else
Upgrade every decision variable utilizing $leapup$ in Eq (12)
end if
end for
end while

Algorithm 1 provides the LO technique, which begins emerging a group with lemurs at random.

Then, it attempts to travel near the lemur with a lesser value of fitness at each iteration over dance hup, as a superior value of fitness. The optimization process begins at random by creating a collection of lemurs. The FRR value begins close to LRR, signifying that the lemur travels and moves near the finest adjacent one by employing dancehup. Now, the LO executes the dancehup act to decrease the values of FRR near HRR. Next, it employs leapup act and suggests the lemur near the finest global solution. These actions will be repeated until the last criterion is satisfied.

Table 1 summarizes the key hyperparameters optimized using the LO method. It outlines the specific parameters, namely learning rate, batch size, dropout rate, and number of LSTM units, with their respective search spaces, illustrating the range of values explored during optimization. This highlights how the LO technique effectively fine-tunes critical model parameters, contributing to improved accuracy and robustness in fire detection.

Table 1. Key hyperparameters optimized by the LO model, including their search spaces and selected optimal values.

Hyperparameter	Search Space	Optimized Value
LEARNING_RATE	[0.0001, 0.01]	0.0012
BATCH_SIZE	[16, 32, 64, 128]	32
DROPOUT_RATE	[0.1, 0.5]	0.3
LSTM_UNITS	[32, 64, 128, 256]	128

The fitness selection is a significant feature that manipulates the performance of the LO technique. The hyperparameter choice procedure adds to the solution encoder model to assess the efficiency of the candidate solutions. In this section, the LO model considers accuracy as the main condition for designing the fitness function, as expressed below:

$$Fitness = \max\left(Accu_y\right). \tag{13}$$

$$Accu_y = \frac{TP+TN}{TP+TN+FP+FN}. \tag{14}$$

Here, TP and FP signify the true and false positive values, and TN and FN specify the true and false negative values.

4. Experimental validation

The performance evaluation of the EFDBVCP-AILOA technique was examined under the fire detection dataset [32] (https://www.kaggle.com/datasets/kabilan03/fire-detection-dataset/data)/ doi: 10.3390/f14091697. The dataset contains 1000 images under dual classes, as represented in Table 2. The suggested technique is simulated by employing the Python 3.6.5 tool on a PC i5-8600k, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter settings are provided as follows: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

Table 2. Details of the dataset.

Classes	No. of Images
Fire	500
Non-Fire	500
Total Images	1000

Figure 3 displays the classifier result of the EFDBVCP-AILOA method under 70% TRPH and 30% TSPH. Figures 3(a) and 3(b) demonstrates the confusion matrices with accurate identification and classification of Fire and Non-Fire classes. Figure 3(c) demonstrates the PR analysis, indicating higher performance across Fire and Non-Fire classes. Figure 3(d) shows the ROC graphs, signifying capable outcomes with high ROC analysis for distinct Fire and Non-Fire classes.

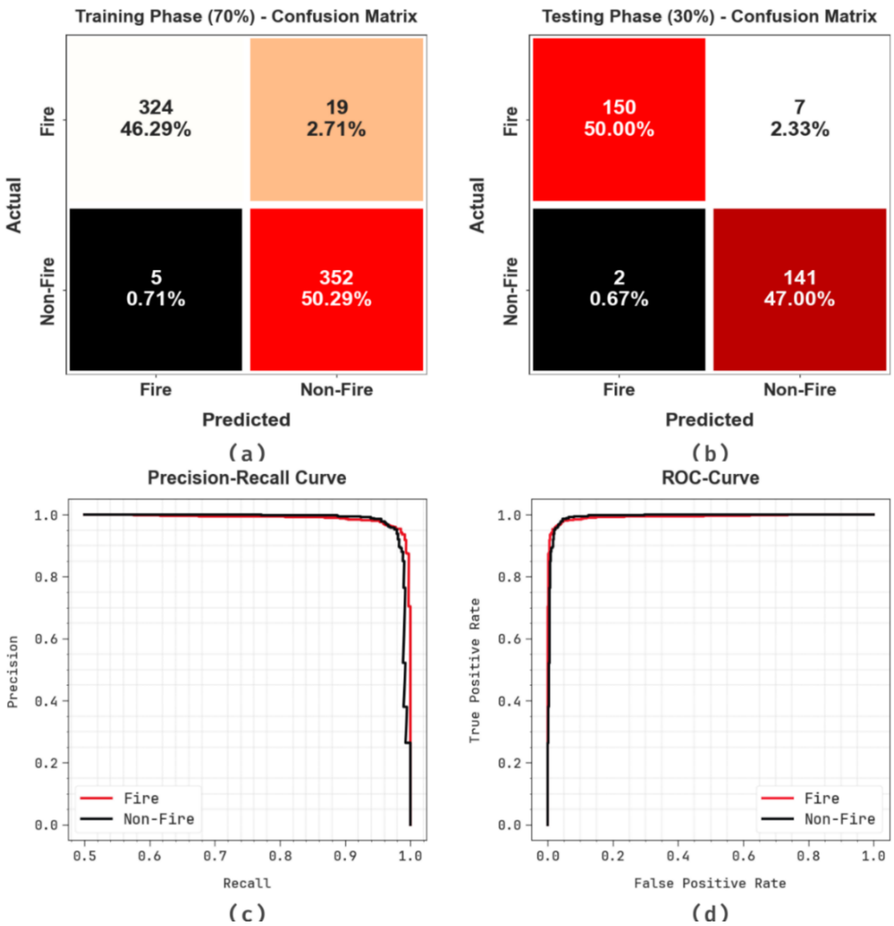

Figure 3. Classifier results of (a-b) 70% TRPH and 30% TSPH confusion matrix, (c) curve of PR, and (d) curve of ROC.

Table 3 and Figure 4 describe the fire detection study of the EFDBVCP-AILOA approach with 70% training phase (TRPH) and 30% of testing phase (TSPH). The results showed that the EFDBVCP-AILOA approach obtains effective detection and classification of each sample. On 70%TRPH, the EFDBVCP-AILOA technique gains an average $accu_y$ of 96.53%, $prec_n$ of 96.68%, $reca_l$ of 96.53%, $F_{measure}$ of 96.57%, MCC of 93.21%, and Kappa of 93.27%.

Furthermore, based on 30% TSPH, the EFDBVCP-AILOA technique reaches an average $accu_y$ of 97.07%, $prec_n$ of 96.98%, $reca_l$ of 97.07%, $F_{measure}$ of 97.00%, MCC of 94.05%, and Kappa of 94.12%.

Table 3. Fire detection outcome of EFDBVCP-AILOA method under 70%TRPH and 30%TSPH.

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$	MCC	Kappa
TRPH of 70%						
Fire	94.46	98.48	94.46	96.43	93.21	93.27
Non-Fire	98.60	94.88	98.60	96.70	93.21	93.28
Average	96.53	96.68	96.53	96.57	93.21	93.27
TSPH of 30%						
Fire	95.54	98.68	95.54	97.09	94.05	94.13
Non-Fire	98.60	95.27	98.60	96.91	94.05	94.12
Average	97.07	96.98	97.07	97.00	94.05	94.12

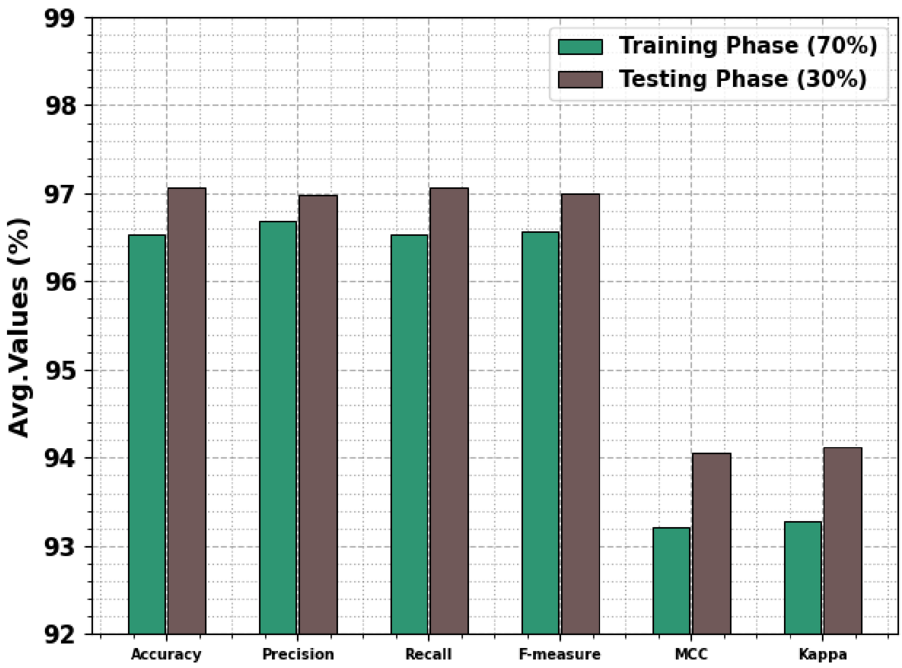

Figure 4. Average of the EFDBVCP-AILOA method under 70% TRPH and 30% TSPH.

In Figure 5, the training accuracy (TRAAC) and validation accuracy (VLAAC) analysis of the EFDBVCP-AILOA approach is revealed. The $accu_y$ values are computed over the range of 0–25 epoch counts. The figure highlighted that the TRAAC and VLAAC graphs demonstrated growing tendencies, which showing the capacity of the EFDBVCP-AILOA approach with higher performance over several iterations. Besides, the TRAAC and VLAAC analysis are adjacent across the epoch counts, which specifies lower overfitting and illustrates enhanced outcomes of the EFDBVCP-AILOA model, guaranteeing reliable prediction on hidden instances.

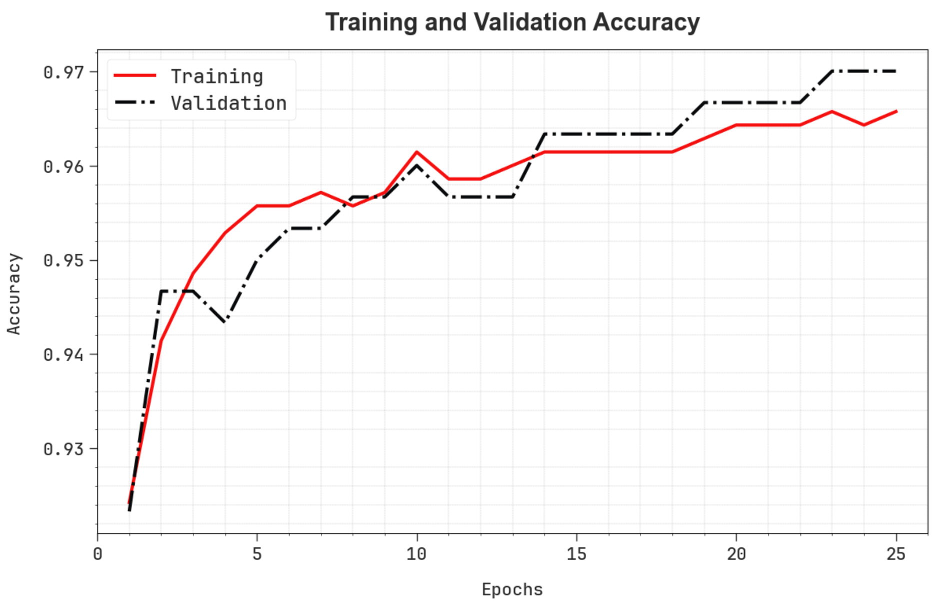

Figure 5. $Accu_y$ graph of the EFDBVCP-AILOA method.

In Figure 6, the TRA loss (TRALOS) and VLA loss (VLALOS) analysis of the EFDBVCP-AILOA approach is demonstrated. The values of loss are computed throughout 0-25 epoch counts. It is noted that the TRALOS and VLALOS values depict a decreasing tendency, showing the capacity of the EFDBVCP-AILOA method to balance a trade-off between data fitting and generalization. The persistent fall in values further proves the maximum performance of the EFDBVCP-AILOA method, which is also capable of tuning the prediction results on time.

Figure 6. Loss curve of the EFDBVCP-AILOA method.

The comparative results of EFDBVCP-AILOA methodology with existing techniques are shown in Table 4 and Figure 7 [33,34]. The result stated that the EFDBVCP-AILOA methodology outperform maximal performances. Based on $accu_y$, the EFDBVCP-AILOA methodology has better $accu_y$ of 97.07% whereas FireNet Algorithm, Fire Detection, OctFiResNet, KutralNext+ Model, Conv layer, and Inception methodologies achieve lower $accu_y$ of 78.85%, 80.85%, 84.00%, 90.46%, 95.39%, 96.08%, respectively. Based on $prec_n$, the EFDBVCP-AILOA technique has a maximum $prec_n$ of 96.98%. At the same time, the FireNet Algorithm, Fire Detection, OctFiResNet, KutralNext+ Model, Conv layer, and Inception methodologies obtained lower $prec_n$ of 89.09%, 84.73%, 92.15%, 86.01%, 91.98%, 94.31%, respectively.

Table 4. Comparative results of EFDBVCP-AILOA methodology with existing approaches [33,34].

Methodology	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$
FireNet Algorithm	78.85	89.09	92.29	95.60
Fire Detection	80.85	84.73	85.17	82.38
OctFiResNet	84.00	92.15	87.92	90.38
KutralNext+ Model	90.46	86.01	86.93	89.92
Conv layer Method	95.39	91.98	93.05	95.55
Inception Model	96.08	94.31	91.51	92.41
EFDBVCP-AILOA	97.07	96.98	97.07	97.00

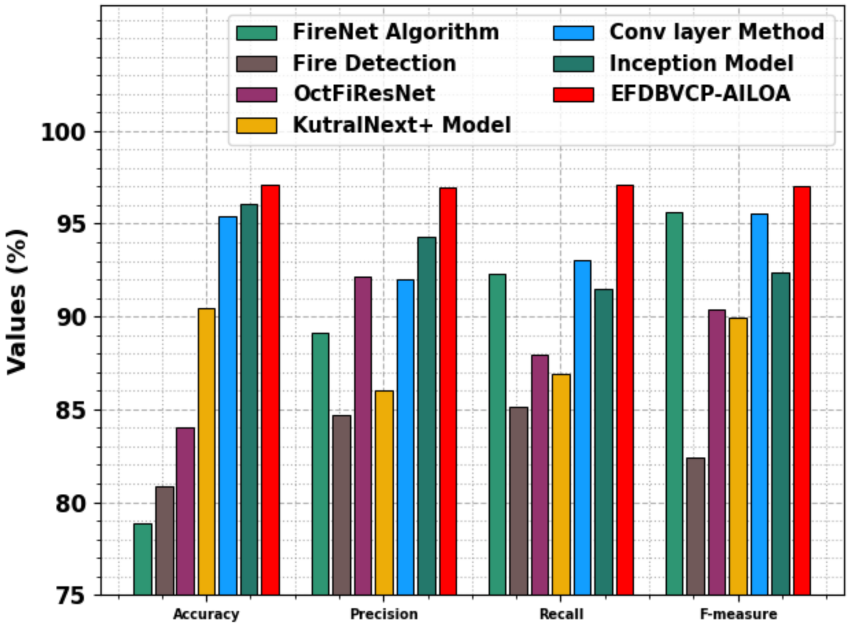

Figure 7. Comparison of the EFDBVCP-AILOA methodology with existing approaches.

Finally, based on $F_{measure}$, the EFDBVCP-AILOA methodology has a maximum $F_{measure}$ of 97.00%, where FireNet Algorithm, Fire Detection, OctFiResNet, KutralNext+ Model, Conv layer, and Inception methodologies achieve decreased $F_{measure}$ of 95.60%, 82.38%, 90.38%, 89.92%, 95.55%, 92.41%, respectively.

Table 5 and Figure 8 show the computational time (CT) analysis of the EFDBVCP-AILOA approach with existing models. The EFDBVCP-AILOA approach records the lowest CT of 10.97 seconds, making it significantly faster than other models such as Inception model with 16.05 seconds, Fire Detection with 18.21 seconds, OctFiResNet with 19.63 seconds, FireNet with 19.85 seconds, Conv layer with 25.79 seconds, and KutralNext+ Model with 27.99 seconds. Such lower CT values highlights the suitability of the EFDBVCP-AILOA model for real-time fire detection applications, specifically in resource-constrained or safety-critical environments. Its fast-processing capability also ensures timely alerts, which is significant for minimizing damage and improving safety measures in such scenarios.

Table 5. CT analysis of EFDBVCP-AILOA approach with existing models.

Methodology	CT (seconds)
FireNet Algorithm	19.85
Fire Detection	18.21
OctFiResNet	19.63
KutralNext+ Model	27.99
Conv layer Method	25.79
Inception Model	16.05
EFDBVCP-AILOA	10.97

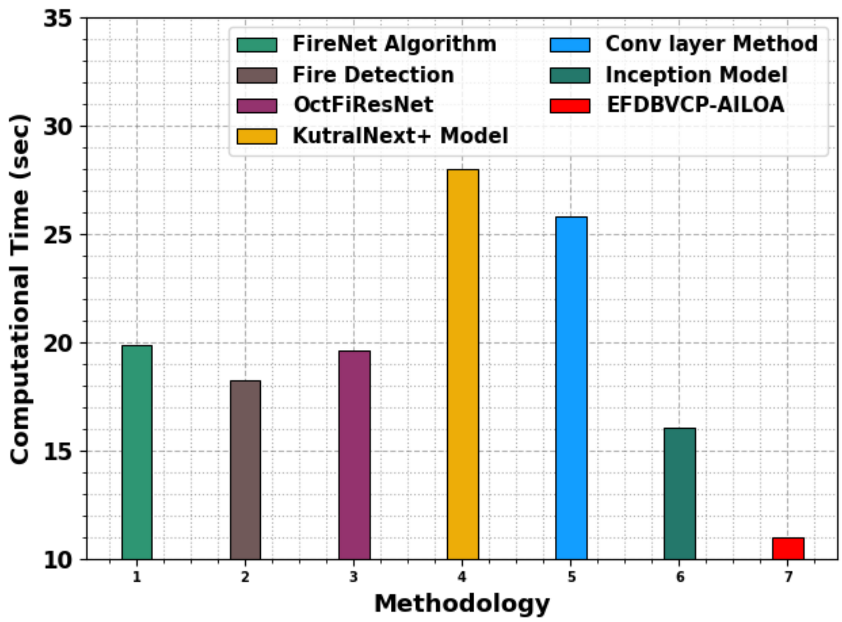

Figure 8. CT analysis of the EFDBVCP-AILOA approach compared with existing models.

Table 6 and Figure 9 specify the error analysis of the EFDBVCP-AILOA method compared with existing models. The EFDBVCP-AILOA method achieves the lowest errors values with an $accu_y$ of 2.93%, $prec_n$ of 3.02%, $reca_l$ of 2.93%, and $F_{measure}$ of 3.00%, clearly outperforming all comparative models. In contrast, higher error values are recorded by other methods such as FireNet with an $accu_y$ error of 21.15% and $F_{measure}$ error of 4.40%, and OctFiResNet with an $accu_y$ of 16.00% and $F_{measure}$ error of 9.62%. The Conv layer and Inception models also exhibit notably higher $F_{measure}$ error of 4.45% and 7.59%, respectively. These findings confirm the robustness and consistency of the EFDBVCP-AILOA model, emphasizing reduced misclassification rates and improved prediction stability across fire detection tasks.

Table 6. Error evaluation of the EFDBVCP-AILOA method with existing techniques.

Method	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$
FireNet Algorithm	21.15	10.91	7.71	4.40
Fire Detection	19.15	15.27	14.83	17.62
OctFiResNet	16.00	7.85	12.08	9.62
KutralNext+ Model	9.54	13.99	13.07	10.08
Conv layer Method	4.61	8.02	6.95	4.45
Inception Model	3.92	5.69	8.49	7.59
EFDBVCP-AILOA	2.93	3.02	2.93	3.00

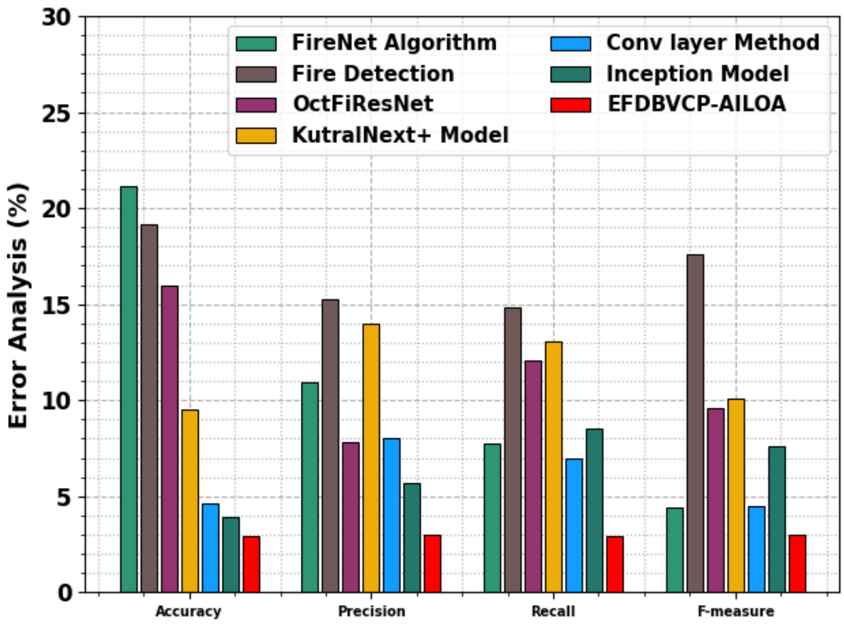

Figure 9. Error evaluation of the EFDBVCP-AILOA method compared with existing techniques.

Table 7 and Figure 10 specify the ablation study of the EFDBVCP-AILOA model. The ABF model achieves an $accu_y$ of 94.61%, $prec_n$ of 94.56%, $reca_l$ of 94.64%, and $F_{measure}$ of 94.59%. Incorporating NASNetMobile for feature extraction improves performance with an $accu_y$ of 95.25% and $F_{measure}$ of 95.18%. Further optimization using the LOA attains an $accu_y$ of 95.81% and $F_{measure}$ of 95.95%, indicating its efficiency in fine-tuning model parameters. When applying CNN-Sa-LSTM for classification, the technique attains an $accu_y$ of 96.49% and a balanced $F_{measure}$ of 96.46%, validating the merit of temporal feature handling and attention. Finally, the EFDBVCP-AILOA technique integrates all these components and attains the highest performance, with an $accu_y$ of 97.07%, $prec_n$ of 96.98%, $reca_l$ of 97.07%, and $F_{measure}$ of 97.00%, confirming that each module substantially contributes to the overall system efficacy.

Table 7. Ablation study-based comparative analysis of the EFDBVCP-AILOA methodology against recent techniques.

Technique	$Accu_y$	$Prec_n$	$Reca_l$	$F_{measure}$
ABF	94.61	94.56	94.64	94.59
NASNetMobile	95.25	95.24	95.16	95.18
LOA	95.81	95.78	95.66	95.95
CNN-Sa-LSTM	96.49	96.36	96.45	96.46
EFDBVCP-AILOA	97.07	96.98	97.07	97.00

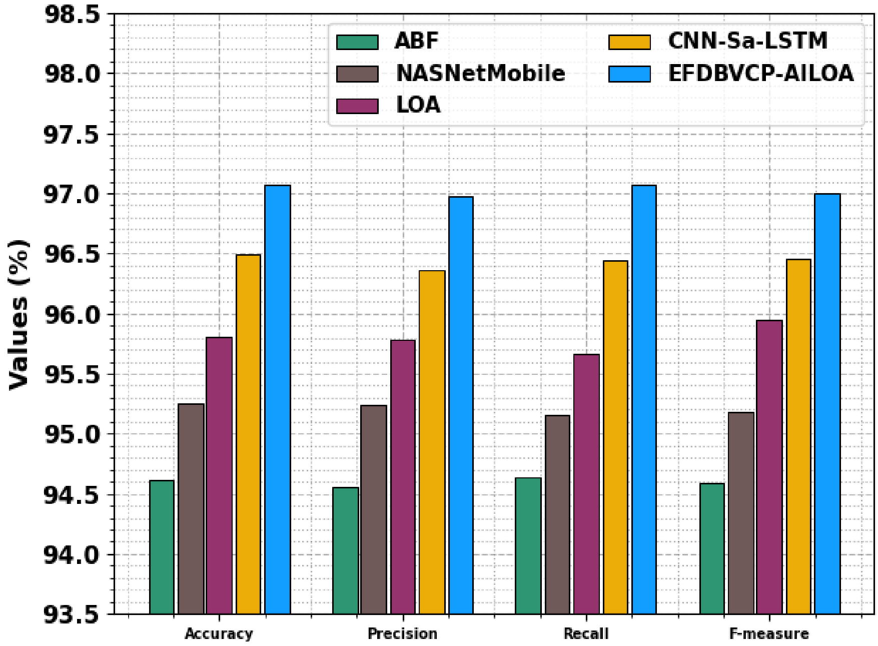

Figure 10. Ablation study-based comparative analysis of the EFDBVCP-AILOA methodology.

Table 8 illustrates the comparative analysis of computational complexity and GPU memory consumption for various fire detection models based on FLOPs and GPU usage [35]. The EFDBVCP-AILOA model attains the lowest computational complexity with only 8.11 GFLOPs and the smallest GPU memory requirement at 934 MB. This depicts its suitability for real-time and resource-constrained environments. In contrast, models such as AGENet-Small and ResNeXt50 demand 29.79 G and 27.68 G FLOPs, respectively, indicating higher computational overhead. Similarly, Inception-v4 consumes the highest GPU memory at 9808 MB, which can be impractical for embedded or edge deployment. Overall, the EFDBVCP-AILOA technique exhibits superior computational efficiency without losing accuracy, making it a crucial solution for practical fire detection applications.

Table 8. Comparative analysis of computational complexity and GPU memory consumption of the EFDBVCP-AILOA technique based on FLOPs and GPU usage.

Models	FLOPs (G)	GPU (M)
Huma Experts	12.50	4973
ResNeXt50	27.68	2399
Inception-v4	14.93	9808
AGENet-Small	29.79	1721
HSCNet	15.78	2043
EFDBVCP-AILOA	8.11	934

Table 9 compares the inference speeds of diverse DL models measured in milliseconds (ms), reflecting their suitability for real-time fire detection scenarios [36]. The EFDBVCP-AILOA model illustrates the fastest inference speed at 10.44 ms, significantly outperforming other prevalent models. VGG16 follows with 16.96 ms, while SqueezeNet exhibits the slowest performance at 30.36 ms. Furthermore, ST and MobileNet take 24.70 ms and 23.32 ms, respectively, depicting higher latency compared to EFDBVCP-AILOA model. These outputs emphasize the lightweight and time-efficient behaviour of the EFDBVCP-AILOA approach, making it suitable for deployment in time-critical and resource-constrained environments.

Table 9. Inference speed comparison of various DL models for fire detection tasks.

Models	Inference Speed (ms)
ResNet152	19.53
MobileNet	23.32
SqueezeNet	30.36
EfficientNet	20.37
VGG16	16.96
Swin Transform	24.70
EFDBVCP-AILOA	10.44

Table 10 presents the RAM requirements of diverse models employed for the fire detection systems, measured in gigabytes (GB) [37]. The EFDBVCP-AILOA methodology requires the highest memory at 16.00 GB, illustrating its complexity and depth. On the contrary, lightweight models like the Transformer and 1D Fully Connected Neural Network (1D FCNN) utilizes only 0.10 GB, making them appropriate for memory-constrained systems. The LSTM model takes 0.90 GB, and the Convolutional SCT Attention model needs 0.50 GB. ResNet models occupy 8.10 GB of RAM, placing them in the mid-to-high memory consumption range. These comparisons clearly underscore the trade-off between model accuracy and computational resources, with the EFDBVCP-AILOA model providing high performance at the cost of increased memory usage. This balance is critical when deploying models in environments where both accuracy and resource efficiency are significant. Precise optimization can assist in building the model to specific application needs without compromising reliability.

Table 10. Memory usage comparison of various models based on RAM consumption for fire detection applications.

RAM	
Model	Memory (GB)
1D FCNN	0.10
ResNets	8.10
LSTM	0.90
Transformer	0.10
Convolutinal SCT Attention	0.50
EFDBVCP-AILOA	16.00

Table 11 compares the latency performance of diverse models based on their frame processing speed, expressed in frames per second (FPs). The EFDBVCP-AILOA approach attains the lowest latency with 2.87 FPs, showing superior real-time efficiency. In contrast, the BERT-base model exhibits the highest latency at 9.55 FPs, followed closely by the SVM at 9.12 FPs and the LR model at 8.92 FPs. MLP and LeNet achieve moderate latency values of 7.28 and 7.30 FPs, respectively, while the RF model exhibits slightly better performance with 6.02 FPs. These outputs highlight the capability of the EFDBVCP-AILOA model for low-latency performance, making it appropriate for real-time fire detection applications where prompt responses are crucial.

Table 11. Latency comparison in FPs for various models in fire detection tasks.

Models	Latency (FPs)
LR Model	8.92
Fandom Forest	6.02
SVM	9.12
MLP	7.28
LeNet	7.30
BERT-base	9.55
EFDBVCP-AILOA	2.87

5. Conclusions

In this paper, an EFDBVCP-AILOA methodology was presented. The EFDBVCP-AILOA technique focused on an advanced fire detection system to assist visually impaired individuals by leveraging DL techniques. Primarily, the EFDBVCP-AILOA technique conducts image pre-processing by using ABF to reduce noise while preserving essential edges in fire images. For the feature extraction process, the NASNetMobile architecture was employed to capture complex features from the image data. Furthermore, the EFDBVCP-AILOA technique implemented the CNN-Sa-LSTM method for classification. Finally, the LO model was used as a parameter-tuning approach for the CNN-Sa-LSTM technique. To demonstrate the improved classification result of the EFDBVCP-AILOA method, extensive experimentation was conducted on a benchmark dataset. The comparative results of the EFDBVCP-AILOA method exhibited a superior accuracy value of 97.07% over existing techniques.

5.1. Limitations and directions for further improvement

The limitations of the EFDBVCP-AILOA method lie on its dependency on a specific dataset, which may limit the generalization of the fire detection system to other environments or conditions. The performance of the model could be affected by discrepancies in lighting, weather, or image quality, which may result in inaccuracies in specific situations. Furthermore, the real-time processing capabilities of the system may require additional optimization for large-scale deployment in resource-constrained settings. Future work should focus on expanding the dataset to encompass a broader range of fire scenarios and environmental conditions. Improving the robustness of the system to dynamic environments, such as varying lighting and smoke, would enhance its reliability. Furthermore, exploring more effective models for faster detection and reducing computational overhead would benefit real-time applications. Lastly, incorporating multimodal sensing technologies could complement visual data for more comprehensive fire detection.

Author contributions

Fahd N. Al-Wesabi: conceptualization, methodology, validation, investigation, writing-original draft preparation; Abdulaziz Alhefdhi: conceptualization, methodology, writing-original draft preparation, writing-review and editing. All authors have read and agreed to the published version of the manuscript.

Use of Generative-AI tools declaration

The authors declare that they have not used Artificial Intelligence (AI) tools in the creation of this article.

Data availability statement

The data that support the findings of this study are openly available in the Kaggle repository at https://www.kaggle.com/datasets/kabilan03/fire-detection-dataset/data, reference number [32].

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Conflict of interest

The authors declare no conflicts of interest.

References

1. F. Khan, Z. G. Xu, J. L. Sun, F. M. Khan, A. Ahmed, Y. Zhao, Recent advances in sensors for fire detection, *Sensors*, **22** (2022), 3310. https://doi.org/10.3390/s22093310

2. A. H. Altowaijri, M. S. Alfaifi, T. A. Alshawi, A. B. Ibrahim, S. A. Alshebeili, A privacy-preserving IoT-based fire detector, *IEEE Access*, **9** (2021), 51393–51402. https://doi.org/10.1109/ACCESS.2021.3069588
3. O. K. Abbas, F. Abdullah, N. A. M. Radzi, A. D. Salman, New adaptive-clustered routing protocol for indoor fire emergencies using hybrid CNN-BiLSTM model: development and validation, *Journal of Intelligent Systems and Internet of Things*, **14** (2025), 08–24. https://doi.org/10.54216/JISIoT.140202
4. Z. Fadhel, H. Attia, Y. H. Ali, Optimized and comprehensive fake review detection based on Harris Hawks optimization integrated with machine mearning techniques, *Journal of Cybersecurity & Information Management*, **15** (2025), 11–21. https://doi.org/10.54216/JCIM.150102
5. A. Jadon, M. Omama, A. Varshney, M. S. Ansari, R. Sharma, FireNet: A specialized lightweight fire & smoke detection model for real-time IoT applications, 2019, arXiv:1905.11922.
6. L. M. Yuan, R. A. Thomas, J. H. Rowland, L. H. Zhou, Early fire detection for underground diesel fuel storage areas, *Process Saf. Environ.*, **119** (2018), 69–74. https://doi.org/10.1016/j.psep.2018.07.022
7. M. Altaee, A. Talib, M. A. Jalil, J. Ali, T. A. Alalwani, Intelligent multi-level feature fusion using remote sensing and CNN image classification algorithm, *Journal of Intelligent Systems & Internet of Things*, **9** (2023), 36–48. https://doi.org/10.54216/JISIoT.090103
8. A. Ayala, B. Fernandes, F. Cruz, D. Macedo, A. L. I. Oliveira, C. Zanchettin, KutralNet: A portable deep learning model for fire recognition, *2020 International Joint Conference on Neural Networks (IJCNN)*, Glasgow, UK, 2020, 1–8. https://doi.org/10.1109/IJCNN48605.2020.9207202
9. K. Muhammad, J. Ahmad, I. Mehmood, S. Rho, S. W. Baik, Convolutional neural networks based fire detection in surveillance videos, *IEEE Access*, **6** (2018), 18174–18183. https://doi.org/10.1109/ACCESS.2018.2812835
10. J. Gotthans, T. Gotthans, R. Marsalek, Deep convolutional neural network for fire detection, *2020 30th International Conference Radioelektronika (RADIOELEKTRONIKA)*, Bratislava, Slovakia, 2020, 1–6. https://doi.org/10.1109/RADIOELEKTRONIKA49387.2020.9092344
11. Z. Y. Yang, M. Gao, J. Choi, Smart walking cane based on triboelectric nanogenerators for assisting the visually impaired, *Nano Energy*, **124** (2014), 109485. https://doi.org/10.1016/j.nanoen.2024.109485
12. I. M. Kamal, M. Salah Abd-elhafeez, A. Farghal, Camera-based navigation system for blind and visually impaired people, *Sohag Engineering Journal*, **3** (2023), 1–13.
13. T. Sugashini, G. Balakrishnan, Visually impaired object segmentation and detection using hybrid Canny edge detector, Hough transform, and improved momentum search in YOLOv7, *Signal Image Video P*, 18 (2024), 251–265. https://doi.org/10.1007/s11760-024-03149-6
14. Y. Said, M. Atri, M. A. Albahar, A. Ben Atitallah, Y. A. Alsariera, Obstacle detection system for navigation assistance of visually impaired people based on deep learning techniques, *Sensors*, **23** (2023), 5262. https://doi.org/10.3390/s23115262
15. L. Kumar, A. S. Kushwaha, A. Jain, An auditory system interface for augmented accessibility: empowering the visually impaired, *Eng. Proc.*, **62** (2024.), 8. https://doi.org/10.3390/engproc2024062008
16. B. Kuriakose, R. Shrestha, F. E. Sandnes, DeepNAVI: A deep learning based smartphone navigation assistant for people with visual impairments, *Expert Syst. Appl.*, **212** (2023), 118720. https://doi.org/10.1016/j.eswa.2022.118720

17. N. Yunusov, B. M. S. Islam, A. Abdusalomov, W. Kim, Robust forest fire detection method for surveillance systems based on you only look once version 8 and transfer learning approaches, *Processes*, **12** (2024), 1039. https://doi.org/10.3390/pr12051039
18. F. N. Al-Wesabi, A. A. K. Alharbi, I. Yaseen, An advanced fire detection system for assisting visually challenged people using recurrent neural network and seahorse optimizer algorithm, *Sci. Rep.*, **15** (2025), 21493. https://doi.org/10.1038/s41598-025-91829-9
19. S. Chitram, S. Kumar, S. Thenmalar, Enhancing fire and smoke detection using deep learning techniques, *Eng. Proc.*, **62** (2024), 7. https://doi.org/10.3390/engproc2024062007
20. A. S. Buriboev, A. Abduvaitov, H. S. Jeon, Integrating color and contour analysis with deep learning for robust fire and smoke detection, *Sensors*, **25** (2025), 2044. https://doi.org/10.3390/s25072044
21. A. S. Buriboev, K. Rakhmanov, T. Soqiyev, A. J. Choi, Improving fire detection accuracy through enhanced convolutional neural networks and contour techniques, *Sensors*, **24** (2024), 5184. https://doi.org/10.3390/s24165184
22. D. C. Sujatha, P. Singh, C. Vallikannu, R. Varman, M. G. Skanda, T. Gavaskar, Enhanced fire detection for industrial and environmental safety using iot-integrated vision sensors and residual clutch attention network and depthwise distinguishable convolutional neural networks, *2025 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*, Bengaluru, India, 2025, 627–632. https://doi.org/10.1109/IDCIOT64235.2025.10914734
23. O. Said, B. M. Hamza, M. Hibatallah, E. M. Ali, E. A. Abdellatif, Low-cost real-time fire detection in smart cities: logistic regression is all you need, *2024 Mediterranean Smart Cities Conference (MSCC)*, Martil-Tetuan, Morocco, 2024, 1–6. https://doi.org/10.1109/MSCC62288.2024.10697062
24. S.-J. Lee, H.-S. Yun, Y.-B. Sim, S.-H. Lee, Design and validation of an edge-ai fire safety system with smartthings integration for accelerated detection and targeted suppression, *Appl. Sci.*, **15** (2025), 8118. https://doi.org/10.3390/app15148118
25. B. Wang, G. Z. Huang, H. X. Li, X. L. Chen, L. Zhang, X. H. Gao, Hybrid CBAM-EfficientNetV2 fire image recognition method with label smoothing in detecting tiny targets, *Mach. Intell. Res.*, **21** (2024), 1145–1161. https://doi.org/10.1007/s11633-023-1445-5
26. M. Khan, N. K. Mahala, P. Kumar, Leveraging mixed data cnn-lstm with fractional order optical flow for early fire detection and xai-guided segmentation, submitted for publication.
27. N. Jahan, T. B. M. Niloy, J. F. Silvi, M. Hasan, I. J. Nashia, R. Khan, Development of an IoT-based firefighting drone for enhanced safety and efficiency in fire suppression, *Meas. Control*, **57** (2024), 1464–1479. https://doi.org/10.1177/00202940241238674
28. H. P. Yu, F. Z. He, Y. T. Pan, A scalable region-based level set method using adaptive bilateral filter for noisy image segmentation, *Multimed. Tools Appl.*, **79** (2020), 5743–5765. https://doi.org/10.1007/s11042-019-08493-1
29. A. W. A. Ameer, P. Salehpour, M. Asadpour, Deep transfer learning for lip reading based on nasnetmobile pretrained model in wild dataset, *IEEE Access*, **13** (2024), 11623–11638. https://doi.org/10.1109/ACCESS.2024.3470521
30. A. Baihan, A. I. Alutaibi, Mohammed Alshehri, S. K. Sharma, Sign language recognition using modified deep learning network and hybrid optimization: A hybrid optimizer (HO) based optimized CNNSa-LSTM approach, *Sci. Rep.*, **14** (2024), 26111. https://doi.org/10.1038/s41598-024-76174-7

31. R. M. Al-Khatib, N. E. A. Al-qudah, M. S. Jawarneh, A. Al-Khateeb, A novel improved lemurs optimization algorithm for feature selection problems, *J. King Saud Univ.-Com.*, **35** (2023), 101704. https://doi.org/10.1016/j.jksuci.2023.101704
32. *Fire detection dataset*, Kaggle. Available from: https://www.kaggle.com/datasets/kabilan03/fire-detection-dataset/data.
33. D.-L. Nguyen, M. D. Putro, K.-H. Jo, Lightweight convolutional neural network for fire classification in surveillance system, *IEEE Access*, **11** (2023), 101604–101615. https://doi.org/10.1109/ACCESS.2023.3305455
34. A. Ayala, B. J. T. Fernandes, F. Cruz, D. Macedo, C. Zanchettin, Convolution optimization in fire classification, *IEEE Access*, **10** (2022), 23642–23658. https://doi.org/10.1109/ACCESS.2022.3151660
35. Z.-Y. Zhang, C.-X. Yan, Q.-M. Min, Y.-X. Zhang, W.-F. Jing, W.-X. Hou, et al., Leverage effective deep learning searching method for forensic age estimation, *Bioengineering*, **11** (2024), 674. https://doi.org/10.3390/bioengineering11070674
36. I. J. Ratul, Y. X. Zhou, K. C. Yang, Accelerating deep learning inference: A comparative analysis of modern acceleration fameworks, *Electronics*, **14** (2025), 2977. https://doi.org/10.3390/electronics14152977
37. Y. Sun, S. Brockhauser, P. Hegedűs, Comparing end-to-end machine learning methods for spectra classification, *Appl. Sci.*, **11** (2021), 11520. https://doi.org/10.3390/app112311520