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# Squirrel search method for deep learning-based anomaly identification in videos

**Laxmikant Malphedwar, Thevasigamani Rajesh Kumar**
Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India

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**ABSTRACT**

The monitoring of human behavior and traffic surveillance in various locations has become increasingly important in recent years. However, identifying abnormal activity in real-world settings is a challenging task due to the many different types of worrisome and abnormal actions, including theft, violence, and accidents. To address this issue, this paper proposes a new framework for deep learning-based anomaly identification in videos using the squirrel search algorithm and bidirectional long short-term memory (BiLSTM). The proposed method combines the squirrel search algorithm, an optimization technique inspired by nature, with BiLSTM for anomaly recognition. The framework uses the knowledge gained from a sequence of frames to categorize the video as either typical or abnormal. The proposed method was exhaustively tested in several benchmark datasets for anomaly detection to confirm its functionality in challenging surveillance circumstances. The results show that the proposed framework outperforms existing methods in terms of area under curve (AUC) values, with a test set AUC score of 93.1%. The paper also discusses the importance of feature selection and the benefits of using BiLSTM over traditional unidirectional long short-term memory (LSTM) models for anomaly detection in videos. Overall, the proposed framework provides a highly precise computerization of the system, making it an effective tool for identifying abnormal human behavior in surveillance footage.



***Corresponding Author:***

Laxmikant Malphedwar
Department of Computer Science and Engineering, Saveetha School of Engineering
Saveetha Institute of Medical and Technical Sciences
Chennai, Tamil Nadu, 602105, India
Email: laxmikant5656@gmail.com

## 1. INTRODUCTION

Surveillance is the method used to keep an eye on people's behavior and actions to manage and safeguard them. Due to its wide variety of uses, particularly wide-area surveillance and health monitoring, automatic detection of anomalous occurrences in video has received much attention recently. Because an anomaly is unknown beforehand and can result from strange behaviors or activities performed in unfamiliar situations, this challenge differs from event detection, where the event is specified. Using internet of things (IoT) gadgets like closed-circuit television (CCTV) cameras is the most common way to observe the number of particles from a distance. Artificial intelligence is implemented in IoT devices to improve quality of life [1], [2]. Numerous CCTV cameras have recently been placed in various public and private spaces for security, traffic monitoring, and other purposes. These cameras can assist in spotting irregularities and taking appropriate action [3]. Anomaly detection is currently a hot topic for academics in a variety of fields, including business, and industry [4]–[6]. The properties of both public and private assets can be protected and saved with the use of anomaly detection. Security-related uses for surveillance cameras include spotting odd behavior or abnormalities in both public and private spaces [7], [8]. Real-time video analysis and suspicious case detection need a IoT of human resources and are susceptible to errors due to a gradual decline in human attention. Several techniques define anomaly activities in the literature as "the occurrence of deviation in regular patterns." The process of choosing a function's decision variables so that the function is at its maximum or minimum value is known as optimization. Numerous real-world engineering issues fall under the category of optimization issues [9]–[11], whereby the decision variables are chosen so that the systems function at their most optimal position. These situations are typically discontinuous, nondifferentiable, multimodal, and nonconvex, making it impossible to use the traditional gradient-based deterministic methods [12]–[14]. In recent decades, a substantial quantity of randomized optimization algorithms [15]–[17] have indeed been created to address the limitations of classical methods. They are motivated mainly by biological behaviors or physical events. Unfortunately, most fundamental metaheuristic algorithms produce unsatisfactory results for complex optimization issues that arise in real-world settings.

The squirrel search method (SSA), enthused by the lively scavenging elegance of flying squirrels, was developed [18]. Because SSA integrates a seasonal monitoring condition, it provides the recompenses of healthier and more effective search space investigation when compared to other algorithms. Additionally, the woodland section has three different tree species (normal, oak, and hickory), which preserves population variety and improves investigation. The performance of SSA is superior to other well-known like genetic algorithm (GA) [19], particle swarm optimization (PSO) [20], bat algorithm (BA) [21], and firefly algorithm (FF) [22]. Then, rather than feeding our classifier model one feature frame at a time, we integrate the characteristics of fifteen subsequent frames by adding up their values [23] weakly supervised techniques bidirectional long short-term memory (BiLSTM) are used to train our classifier model. BiLSTMs are quite beneficial when the background of the information is essential. Information travels from backward to forward in a unidirectional long short-term memory (LSTM). Instead, BiLSTM customs two concealed states to allow data to flow headlong and backward. As a consequence, BiLSTMs are more capable of comprehending the context [24]. The following are the primary accomplishments of the recent study:

- The SSA uses a regular cloud generator to produce new positions for flying squirrels while they are gliding, which also improves the SSA's exploration capability;
- A selection approach amongst successive positions is suggested to keep a flying squirrel individual in the best position possible throughout the optimization process, enhancing the algorithm's ability to exploit different locations.
- Extracted features are subsequently employed for anomaly identification. Therefore we apply the BiLSTM, strengthening the local search capability.

The researchers [25], [26] provided a novel method for describing a person's current behavior condition founded on the location and rapidity of the focus and its surroundings. They made use of the interaction energy potential function. This method used the relationship between a social conduct's action and energy potential to describe social behavior. They employed a support vector machine for this method to classify the unique energy action pattern as an anomaly. This suggested approach uses the connection between a person's present state and their responses.

Direkoglu *et al*. [27] proposed a unique feature-based visual flow for the detection of abnormal crowd behavior. On the pixel level, it operates. This technique looks for unusual behavior using angle deviations at each pixel level. Additionally, it assesses the angle difference between the present frame and the preceding one. A straightforward one-class support vector machine is employed to identify typical behavior. Additionally, they ran tests using the UMN and PETS2009 datasets. The MAP framework was created by Li *et al*. [28] for anomaly identification utilizing prior information. Prior information is combined with the Bayesian framework to identify anomalies. The maximum grid template is used to calculate the likelihood function. In difficult circumstances, this experiment delivers incredibly useful results.

Ullah *et al*. [29] described the pedestrian movement in a congested neighborhood and discovered abnormalities. For the discovery of strange objects and their localization in pedestrian flow, he suggested the Gaussian Kernel based integration model (GKIM) model. He computed the EER and DR between the grid and frame levels. The aberrant entity is found based on its placement in the framing. The human-related crime (HR-crime) dataset was used by Vu *et al*. [30] to figure out the feature removal pipeline for activities that classify human-related abnormalities. A benchmark investigation of HR crime outlier prediction is also provided. Majhi *et al*. [31] technique for handling abnormality in a single model uses a weakly supervised learning approach. I3D is many to many [32] LSTM was used for feature extraction, with an area under curve (AUC) value of 82.12%.

Robust temporal feature magnitude (RTFM) learning is a novel method proposed by Tian *et al*. [33] to considerably improve the resilience of the MIL strategy to undesirable events from abnormal films. To correctly identify the successful examples in RTFM, a characteristic magnitude learning algorithm must be trained. RTFM was carried out using the temporal feature magnitude of the video samples. Cao *et al*. [34] recommended using an adaptive graph convolutional network (GCN) to find video anomalies. The recommended technique builds a global graph while taking feature similarity into interpretation.

## 2. METHOD

### 2.1. Proposed workflow

The stages of the planned method are as trails:

- The SSA increases its capacity for exploration by using a regular cloud generator to provide new sites for flying squirrels while it is gliding.
- To retain a flying squirrel personality's optimum position during the optimization process, a selection method between succeeding locations is suggested, which improves the algorithm's capacity to be exploited. Thus, the local search capability is strengthened using a search improvement technique.
- Extracted features are then employed to identify anomalies, hence we adopt the BiLSTM architectural framework. Figure 1 is a visual representation of the methodology used in the proposed approach. It provides an overview of the steps involved in the proposed approach for anomaly detection in videos.

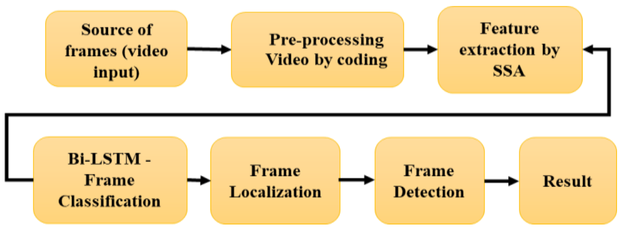


Figure 1. Method

### 2.2. Squirrel search optimization algorithm

SSA impressionists the positive feeding behavior of flying squirrels in deciduous woods of Europe and Asia by gliding for long-distance migration [18]. Squirrels navigate the forest for food sources during warm weather by gliding from one tree to another. They can easily detect acorn nuts to meet their daily energy necessities. The best food supply kept for the winter, hickory nuts, are then sought for. Although they are less energetic in the winter, they store hickory nuts for energy. The activity of flying squirrels grows as the temperature improves. The procedure above is repeated and keeps going over the squirrels' whole life span, forming the basis of the SSA. The following mathematical steps can be used to model the optimization SSA by the flying squirrels' method of food gathering.

#### 2.2.1. Initialize the algorithm parameters and establish the positions and sorting of flying squirrels

The population size NP, the maximum number of iterations $Itermax$, the number of choice variables n, the likelihood of a predator's existence $Pdp$, the scaling factor sf, the gliding constant Gc, and the lower and upper limits for objective functions $FSU$ and $FSL$ are the chief constraints. These conditions are established at the start of the process.

The search tempo initializes the flying squirrels' positions at randomized as (1):

$$FS_{i,j} = FS_L + rand\,() * (FS_U - FS_L), \tag{1}$$

$$i = 1,2,\ldots,NP, j = 1,2,\ldots,n$$

where rand() revenues an arbitrary quantity.

Adding the value of choice variables into a fitness function yields the fitness value $f$=($f1f2, \ldots, fNP$) of a particular flying squirrel's location:

$$f_i = f_i\left(FS_{i,1}, FS_{i,2}, \ldots, FS_{i,n}\right), i = 1,2,\ldots,NP \tag{2}$$

Then, the suitability rate of the flying squirrels' positions is used to rank the food excellence sources in increasing order:

$$[sorted\_f, sorte\_index] = sort\ (f) \tag{3}$$

Tri sorts of trees are categorized subsequently categorizing the food foundations of each flying squirrel's habitat: hickory trees (which are a source of hickory nuts), oak trees (which are a source of acorn nuts), and regular trees. The best food source (i.e., the one with the lowest fitness value) is believed to be located in a hickory nut tree ($FSht$), the subsequent tri food bases are made-up to be located of acorn nut trees ($FSat$), and the remaining sources are supposed to be located in standard trees ($FSnt$):

$$FSht = FS\ (sorte\ index\ (1)) \tag{4}$$

$$FS\ at\ (1{:}\ 3) = FS\ (sorte\ index\ (2{:}\ 4)) \tag{5}$$

$$FS\ nt\ (1{:}\ NP - 4) = FS\ (sorte\ index\ (5{:}\ NP) \tag{6}$$

### 2.2.2. Produce new locations through gliding

After the flying squirrels' procedure, three situations might manifest.

Scenario 1: Hickory nut trees are likely to be approached by flying squirrels on acorn nut trees. The following is a method for creating the new locations:

$$FS_{at}^{new} = \begin{cases} FS_{at}^{old}, d_g G_c\left(FS_{ht}^{old} - FS_{at}^{old}\right), if\ R_1 \geq P_{dp} \\ random\ location\ , otherwise \end{cases} \tag{7}$$

$R1$ is a purpose that returns a number, $dg$ is the random gliding distance, and $Gc$ is the gliding constant.

Scenario 2: approximately accumulators on regular trees would shift to an acorn nut tree to get their daily liveliness necessities met. The resulting is a method for creating the new locations:

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old}, d_g G_c(FS_{at}^{old} - FS_{nt}^{old}), if\ R_2 \geq P_{dp} \\ random\ location\ , otherwise \end{cases} \tag{8}$$

where $R2$ is a function that takes an input from the [0, 1] range and produces a value.

Scenario 3: approximately hovering collectors on regular trees might go to a hickory nut tree if their daily energy needs have been met. The following formula can be used to determine the new position of squirrels in this scenario:

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old}, d_g G_c\left(FS_{ht}^{old} - FS_{nt}^{old}\right), if\ R_3 \geq P_{dp} \\ random\ location\ , otherwise \end{cases} \tag{9}$$

where $R3$ is a purpose that yields a value on the range [0, 1] from a uniform distribution.

Gliding distance $dg$ is assumed to be between 9 and 20 meters in all circumstances [18]. The algorithm may perform poorly because this value is relatively huge and may introduce significant disturbances. A scaling factor ($sf$), whose value is set to 18 [18], is inserted as a divisor of $dg$ in order to achieve the algorithm's desired performance.

### 2.2.3. Examine the current state of the programme and bring to an end criterion

Seasonal changes $Sc$ have a big impact on flying squirrels' foraging habits.

$$S_c^t = \sqrt{\sum_{k=1}^{n}\left(FS_{at,k}^t - FS_{ht,k}\right)^2}, t = 1,2,3 \tag{10}$$

$$S_{cmin} = \frac{10E-6}{365^{Iter/Iter_{max})/2.5}} \tag{11}$$

Then, the status of the seasonal monitoring is examined. When $S_c^t$<$Scmin$ occurs, the winter is ended.

$$FS_{nt}^{new} = FS_L + Lévy\ (n)\ x\ (FSU - FSL) \tag{12}$$

where Lévy is distribution.

The algorithm terminates if the predetermined quantity of repetitions is reached. If not, the actions of developing new sites and assessing how the periodic tracking is going are reiterated.

### 2.3. BiLSTM

Recurrent neural networks (RNNs) are a type of backward-connected network in which output from one layer is sent back [35]. RNNs preserve state by using the results of calculations made in a prior timestep in the current timestep. RNNs are frequently employed as models where values at earlier time steps might influence the current scheming [36].

As shown in Figure 2, there are two methods for training the BiLSTM memory block: one uses data from the past and present at various points in time, while the other uses data from the future and past. Each layer computes the subsequent function for each constituent in the input sequence. The variable represented by LSTM cell is indicated by (13) to (18):

Input gate: $I_t = \sigma(W_I x_t + A_I h_{t-1} + b_I)$ (13)

Forgot gate: $P_t = \sigma(W_P x_t + A_P h_{t-1} + b_P)$ (14)

Output gate: $O_t = \sigma(W_O x_t + A_O h_{t-1} + b_O)$ (15)

New memory cell: $c_t = W_t c_{t-1} + I_t \tilde{c}_t$ (16)

Final memory cell: $\tilde{c}_t = tanh(W_C x_t + W_C h_{t-1} + b_C)$ (17)

Final output: $h_t = O_t \tanh(c_t)$ (18)

Where $W_I$, $W_P$, $W_O$, and $W_C$ represent input weight vectors, while $A_I$, $A_P$, $A_O$, and $A_C$ represent upper output weight vectors. Then b signifies bias vectors; $\sigma$=sigmoid function.

Since one-way memory is used, the findings of the uni-directional LSTM technique contain certain mistakes [37]–[39]. The BiLSTM approach, an extension of the conventional LSTM approach, can enhance performance in sequence classification (future to past). The two concealed LSTM layers are linked to the output by BiLSTM. This encourages improving the long-term learning reliance, consequently enhancing the model performance. According to a previous study, bidirectional networks are demonstrably superior to regular ones in several areas, including the classification of anomaly video cases. Figure 3 depicts the structure of BiLSTM.

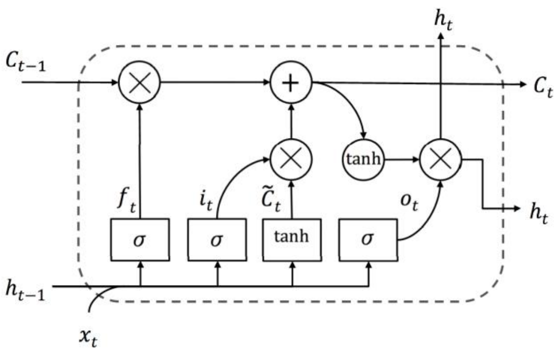


Figure 2. LSTM model

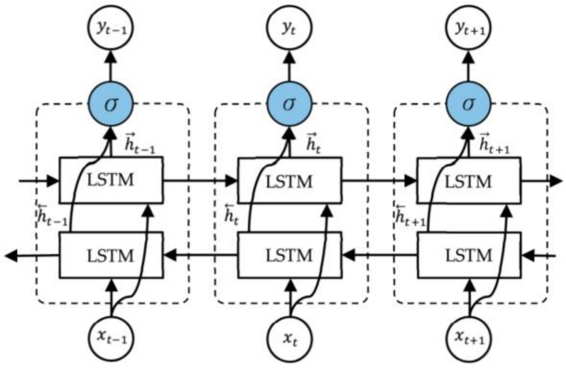


Figure 3. The unfolded architecture of BiLSTM

The recessive LSTM layer output is produced employing the inverted contributions from time t−1 to t−n, just as the forward output waveform is acquired similarly to the unidirectional one. After being supplied to the function, these output sequences were combined into an output vector called yt [40]. The ultimate result can be characterized by a vector, Yt=[yt−n, . . . , yt−1]. The suggested system's thorough procedure is depicted in Figure 4.

The preprocessing of the data and feature extraction using the SSA based on Algorithm 1 are the two steps that make up the SSA-based BiLSTM technique. Merely said, frame recognition is a crucial component of frame categorization since it allows for the accurate location and measurement of an object within an image [41]. Frame localization establishes the position and dimensions of a body [42]. After that, anomalous behavior in the video is discovered using BiLSTM classification of the extracted features.

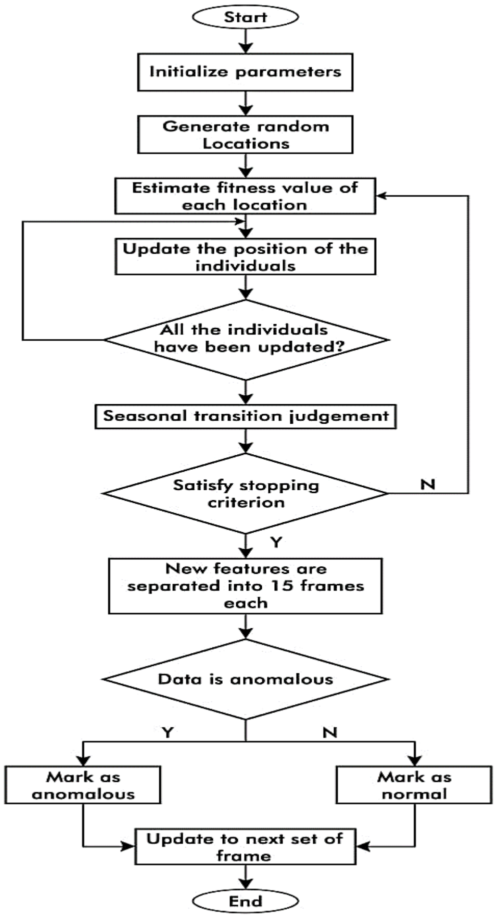


Figure 4. Workflow of the proposed system

Algorithm 1.

```
Set the parameters Iter_max, NP, n, P_dp, sf, G_c, FS_U and FS_L
initialize locations by equation (1)
Compute suitability value by (2)
While Iter < Iter_max
Generate new locations using (3-6)
for t = 1: n1
        if R_1 ≥ P_dp
        Execute condition (i) of equation (7)
        else
        Execute condition (ii)
        end
        end
        for t =1: n2
        if R_2 ≥ P_dp
        Execute condition (i) of equation (8)
        else
        Execute condition (ii)
        end
        end
        for t = 1: n3
        if R_3 ≥ P_dp
        Execute condition (i) of equation (9)
        else
        Execute condition (ii)
        end
        end
        Check Seasonal Monitoring Condition
Compute the suitability value of new locations
        Iter = Iter + 1
end
```

## 3. RESULTS AND DISCUSSION

### 3.1. Dataset and evaluation metric

The experiment uses the avenue dataset, which has 16 training and 21 testing video clips. TensorFlow, a framework for neural network training, was utilized by us [43]. The RNN model's output layer, which divides the entire dataset into two categories—threat and safe consists of just two neurons. The videos included contain several offensive sequences and have not been altered. There are 940 unshuffled frame chunks, extracted in 15 frame batches per 1 second. They are reduced via preprocessing and feature extraction. It is discussed how the present research is compared to the suggested method and evaluated.

### 3.2. Receiver operating characteristic curve

Eighty percent of the data samples are used for the BiLSTM classifier's training, and the remaining twenty percent are used for validation. The receiver operating characteristic (ROC) curve can determine the classifier's overall performance. As seen in Figure 5, the BiLSTM classifier outdoes the LSTM (labeled "LSTM" in the legend) in AUC values. The steps for calculating the ROC and AUC curves are as follows. The negative log of the sequence probability has been computed for each sequence in the validation data for different values:

- The sequence is categorized as an attack (positive) if the negative log value is higher than the threshold, else it is categorized as normal (negative).
- The sequence is designated as TP, FP, TN, or FN.
- A plot of the ROC curve is shown for various threshold levels.
- The ROC curve's AUC value is determined.

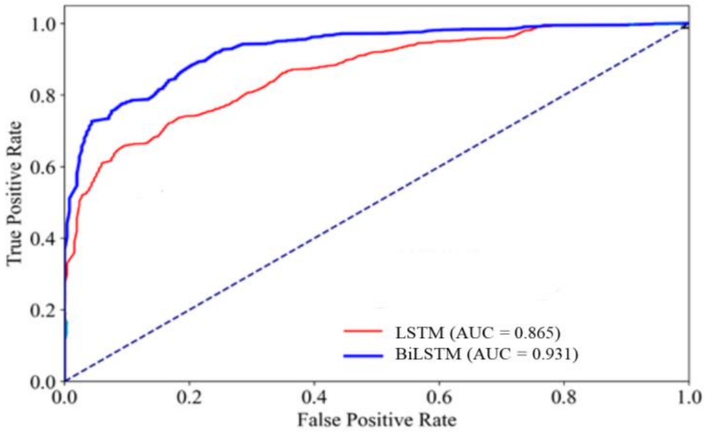


Figure 5. ROC curve for our classifier model

The ROC curve shown demonstrates that compared to other approaches, our method achieved the best AUC of 93.1%. When the AUC value is near 1, the model has a decent capacity to distinguish between normal and anomalous data.

### 3.3. Quantitative results analysis

Accuracy, precision, recall, and F1 measure are the metric characteristics used for evaluation and judgment. Confusion matrix is composed of accuracy=(TP+TN)/(TP+FN+FP+TN), precision=TP/(TP+FP), recall=TP/(TP+FN), and F1=2* precision*recall/(precision+recall). The TP, TN, FP, and FN denote true positive, true negative, false positive, and false negative in classification results. In comparison to other algorithms now in use, such as CNN, F-CNN, LSTM, and the suggested method. Table 1 and Figure 6 give a good image of the best accuracy rate and reduced complexity.

Table 1. Comparing key metrics

| Methods | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| CNN | 89.7 | 84.9 | 81.6 | 82.5 |
| F-CNN | 92.6 | 87.2 | 84.6 | 87.4 |
| LSTM | 96.8 | 97.3 | 85 | 96.5 |
| Bi-LSTM | 98.2 | 97.3 | 95 | 96.5 |

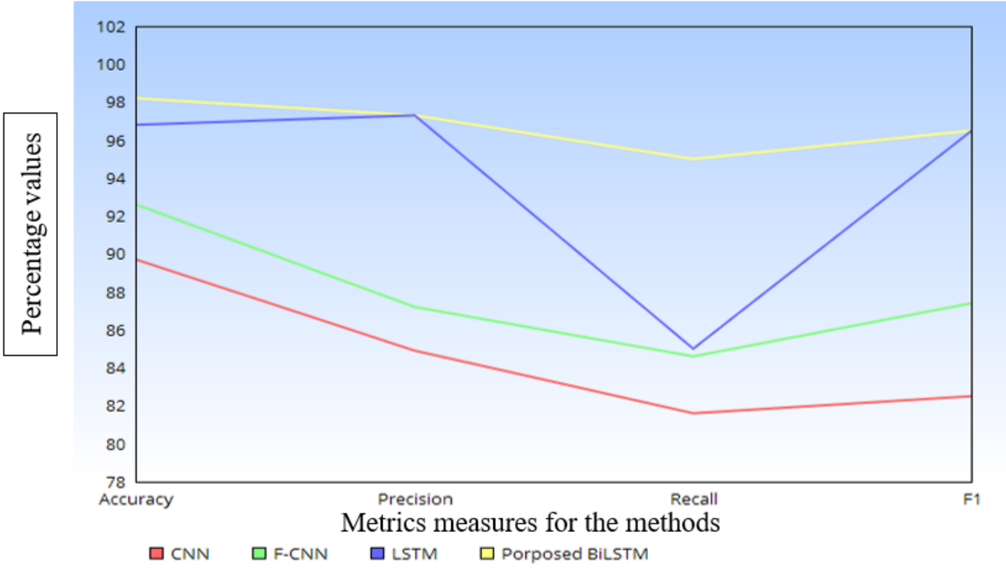


Figure 6. Comparative analysis graph

## 4. CONCLUSION

This research proposes a unique SSA-BiLSTM approach for anomaly identification in video. The SSA is a brand-new method for global search optimization that is based on how flying squirrels find food. The flying behavior of the flying squirrel population is described as being random and fuzzy using the typical cloud model. The selection approach improves a flying squirrel's capacity for local search. Additionally, improving dimensional search produces better iterations of the optimal answer. BiLSTM is used in extensive comparison research to look for anomalies in datasets. ROC curve and AUC calculations are made to demonstrate the BiLSTM's superior performance in anomaly identification. Due to the BiLSTM network's design, which allows input to flow in both directions to retain past and future data, the BiLSTM performs better than the uni-directional LSTM. The combination of SSA and BiLSTM results in better anomaly event detection accuracy. The proposed framework can be integrated with future techniques for scaling, feature selection algorithms, and dimensionality reduction algorithms.

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## BIOGRAPHIES OF AUTHORS

**Laxmikant Malphedwar** received his Bachelor of Engineering degree in Computer Science and Engineering from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad during 2007, Master of Technology degree in Computer Science and Engineering from Jawaharlal Nehru Technological University Hyderabad during 2014 and Ph.D. scholar in Computer Science Engineering from Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India. He is currently working as an Assistant Professor in the Department of Computer Engineering at DR. D. Y. Patil College of Engineering and Innovation Varale Talgaon Pune, Maharashtra India. He has more than 16 years of teaching experience as an undergraduate. He is a life member of IAENG. He can be contacted at email: laxmikant5656@gmail.com.

**Thevasigamani Rajesh Kumar** received his Bachelor of Engineering degree in Electronics and Communication Engineering from Madras University in 1996, a Master of Engineering degree in Computer Science and Engineering from Manonmaniam Sundaranar University in 2004, and a Ph.D. degree in Information and Communication Engineering from Anna University, Chennai during January 2020. He is currently working as an Associate Professor in the Computer Science and Engineering department at Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India. He has more than 20 years of teaching experience at the undergraduate and master-graduate levels. He has published 4 book chapters, 3 Patents, 7 SCIE journals, 32 Scopus papers, and 6 peer review research papers in journals and conferences also authored 1 book. His research area includes speech/image signal processing, machine learning, data mining, embedded systems, and knowledge engineering. He is a life member of ISTE, and a member of IAEng, IACSIT, IRED, CSTA, and ACM. He can be contacted at email: t.rajesh61074@gmail.com.