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ORIGINAL RESEARCH

Novel deep learning framework for broadcasting abnormal events obtained from surveillance applications

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Abstract
Nowadays, wireless sensor networks based applications is drastically increasing. One of the emerging and public safety applications is surveillance monitoring. This paper focused on monitoring a forest environment, is considered as the sample surveillance application. The existing deep learning application has been used only for object detection and classification alone. It does not explain about data transmission or the base platform where the application deployed. But this paper describes the surveillance application and routing in WSN more clearly. Surveillance monitoring is mainly used for identifying and detecting abnormal activities to tighten the security and provide prevention in a specific field. This paper proposed a Novel Deep Learning Framework (NDLF) for integrating two different fields such as image processing and routing in wireless sensor network. NDLF involves a deep Convolution Neural Network for identifying the abnormal events and the data streaming by creating a Multipath routing in WSN. The multipath routing immediately creates an optimal path and transmit the data as quick as possible to the admin, which leads to provide security. NDLF is implemented and experimented using MATLAB software, verify the results and evaluate the performance. From the comparison, it is identified that the proposed NDLF method obtained 99.53% of accuracy in classification, which is better than the existing approaches such as Time-efficient Object Recovery Scheme and a Communication-efficient Object Recovery Scheme. Also, the proposed NDLF performs well than the existing CNN method in terms of precision and recall.

Keywords Deep learning · Convolution neural network · Object detection and classification · Wireless sensor network · Surveillance monitoring applications

1 Introduction

The main moto of this paper is to save forest and various assets in the forest from fire accidents and other natural disasters. To increase the security and providing immediate reaction against abnormal events, an alarm is (alert message) broadcasting the abnormal event. In this paper, a novel deep learning framework (NDLF) is used for abnormal event identification and detection in remote Forest. It helps to save the forest, animals, trees and other assets in the forest. There are two different fields are involved in this framework such as video/image processing and wireless sensor networks. Hence it is necessary to understand the concepts of video/image processing as well as WSN.

Wireless sensor network (WSN) consists of several sensor nodes to monitor the environment where they are deployed geographically. The node can able to sense, process and communicate with each other through a wireless link and can communicate with the base station to the internet and end user. The node transfers the data using the multi-hop technique to communicate with the other nodes and to the sink and gateway to the internet or the other network. The nodes can be stationary or mobile nodes, and it can be homogeneous or heterogeneous nodes, and the network may have a single sink or multi-sink to connect with the base station. The sensor network has the ability of self-organizing and can cooperate with each other to communicate. Each node

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in the WSN has an inbuilt processor to process the raw data before transmitting to others. There are an extensive variety of applications using WSNs ranging from environmental monitoring, military surveillance, object tracking, event detection, healthcare monitoring, structural monitoring, vehicle detection, biomedical field, agriculture field and habitat monitoring.

In environmental monitoring, WSN is used to monitor the environment like sensing the pollution in the air, quality of water, natural disasters, forest fire detection, and landslide detection. In healthcare monitoring, WSN can use as wearable and implantable devices which implanted inside the body. It can use for monitoring the patients in hospital or home thoroughly to examine the behavior of the patient. In agricultural applications, WSN is used to check the condition of the environment which affects crops, soil moisture, humidity of the air, and tracking birds, insects, and animals. In structural monitoring, WSN is used to sense the movements inside the building, bridges, and flyovers. In intelligent home monitoring, WSN provides a smart living environment for the human beings, and it gives more comfort, safety, security, energy saving and automation of the situation. In military applications, WSN is used for surveillance, target system control, and computing, and intelligence. Many of the countries are motivated the research in this field for the intelligent processing of military applications. In industrial applications, WSN is used for monitoring the manufacturing equipment and process to avoid failure. The sensor can locate in unreachable position in machinery to sense temperature, pressure, etc., and to give the alarm in case of failure.

In vehicle detection, WSN is used for tracking and detecting the vehicle using GPS systems, speed control and emergency handling. And also, WSN is used for traffic monitoring on the road and can send the message to the drivers to avoid further traffic. Using RFID along with WSN provides location-based service to track the position of human beings or any object. In this paper, we discussed the animal monitoring using sensors in the forest.

2 Animal monitoring

Life science researchers are focusing on the plants and animals in the wild area with different field conditions. The human presence in the field may distort the results by altering behavioral patterns or distributions, while at worst anthropogenic disturbance can severely reduce or even destroy sensitive populations by increasing stress, decreasing breeding success, increasing predation, or causing a shift to unsuitable habitats. WSN is used widely in habitat monitoring nowadays. The sensors are used to monitor the animal's information in the forest to the base station and to send to the remote station. But it is tough to watch in the remote wild area because of the hazardous and uncertain environment of the forest. And also the energy limitation of the sensors to send the sensed information to the end user timely causes more costly.

The sensor networks in this field provide more benefits when compare to traditional methods of monitoring. Sensors can be deployed in the sensitive area of the forest to monitor the animal activities. This deployment considered as more economical than the other precious methods. Occasionally it may be discomfort and may be some risk to the deployed sensors may happen in the field. Logistics need to be implemented in the forest area during the initial period of node deployment and in a time interval. It may be useful in the long term for studying the habitability of animals and for further research.

Low-cost Sensors can be deployed in the wild area to track and monitor the animals and can detect the wildlife appearance. These sensors can sense the animal's sound, image, and video of the animal and it can send the information to the basestation. This information is time sensitive and cost-effective and mainly used for surveillance. In the remote area deployed sensors can sense the knowledge of animals and it sends to the remote base station may take some time delay. If the information reached to the end user at a particular time interval and at the same time the sensed animal may leave the specific place. So, the primary challenge of this research is the detected information should reach the base station within less time. Each animal has particular features and habitats that will live as a group and move of the animal has a specific pattern. It can predict according to the animal feature and behavior, and we can track those animals with the path prediction method. The following Fig. 1 shows the existing architecture of sensor network for animal monitoring in the forest. Here the sensors are deployed randomly, and it can be self-organized, and it will communicate with each other by multi-hop technique, and the sensed information reaches the base station via the gateway node, and finally, it hosted on the internet for further processing. The surveillance environment is surrounded and monitored by remote measuring stations. Figure 1a is the surveillance environment and (b) shows the entire application. In a surveillance monitoring system, when an abnormality is identified it should be intimated to the admin, server, or associated people in the network immediately. It leads to stop further tragedies in the network. If the abnormality is broadcasted, the person who is near to the location can take necessary action as early as possible to safe the surveillance environment.

In this paper, the surveillance monitoring is assumed as an application and part of WSN. A set of wireless sensor nodes are deployed for monitoring purpose. WSN is the collection of sensor nodes that are connected together in

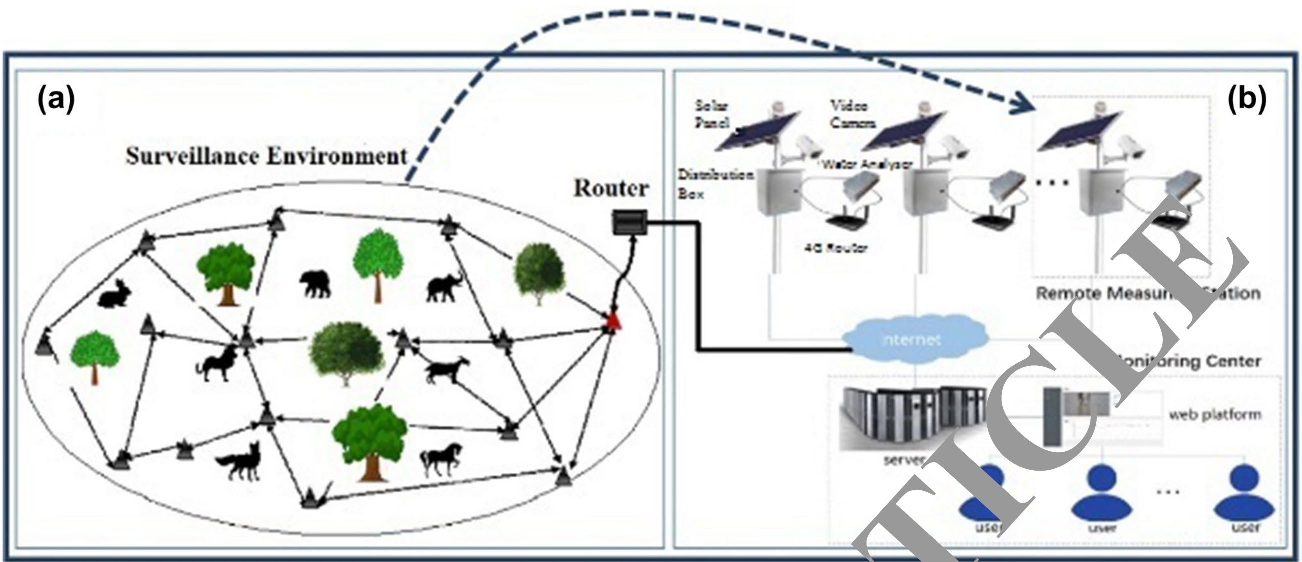

Fig. 1 Surveillance monitoring application of WSN

a network by wireless medium. Sensors are connected to the routers/cluster head/relay station and hence to base station. Figure 1 shows the surveillance application is a part of WSN.

The main objective of this paper is to improve the quality of service of WSN in an emerging application such as surveillance monitoring. To do that, a novel deep learning framework (NDLF) is proposed for learning the network information such as route, data transmitted in the network and to locate an optimal route. The surveillance environment that improves the quality of service in a surveillance monitoring system is an application of WSN. A set of sensor nodes which are placed in the surveillance network is used to monitor the behavior of the objects. Deep learning approach learns the data which is collected from the sensor nodes. Then it identifies the abnormality and pass it to admin for broadcasting. Deep learning method learn, analyse, extract, select and classify the abnormality over the surveillance data. If the abnormality is detected, immediately the routing algorithm is called for broadcasting it. Abnormal identification is obtained by training the deep learning model and used for testing purpose. The abnormal data is alone broadcasted in the network whereas the other data is stored in the nearest data centre for further analysis. The routing protocol is a broadcasting protocol with increased QoS in terms of energy, delay and throughput. In order to save the energy consumption, alternate sensor nodes follow sleep-active mechanism.

To provide a better approach for forest monitoring the following contribution is carried out one by one.

1. Constructing the surveillance monitoring application under WSN environment.
2. Implementing a dCNN model for abnormal event identification by analyzing surveillance data such as video and images.
3. Broadcast the data through a broadcasting routing protocol.

3 Related work

Monitoring the animals in the wild area is the most crucial topic in recent years. So many authorities compel the government to track the animals all over the country. The author in Hsu et al. (2012) introduced an RFID chip called VeriChip is implanted in the animals to monitor the animals. This chip injected into the animal, and it has the size of a grain of rice. The author in Gossett (2004) located the sensor in ducks' underground nests and on four-inch stilts situated immediately outer surface of duck burrows for a nine-month monitoring period. This deployed network of thirty-two nodes continuously streams data onto the web. The researchers at Princeton University (Mainwaring et al. 2002) investigated the wildlife tracking with help of wireless sensor networks. They named this tracking system as Zebranet and the sensed data transferred to the mobile base station using peer-to-peer networking techniques. They used 2.4 lb collars enabled with GPS to worn by the animals to track.

Some of the earlier researchers proposed various approaches for tracking animalsin a remote forest area (Juang et al. 2002; Liu et al. 2003; Shin et al. 2003). Some of the research focused, based on the sensor's received signal with time measurements to signify the location and characteristics of the animal. One approach is to take on the classic Bayesian formulation, which computes the measurement and communication costs to minimize tracking failure. The research work in Zhao et al. (2003) explained about the multiple target tracking environments, monitoring the behavior of various animals. It also used for tracking wolf which will vulnerably attack the innocent lambs. The author in Guibas (2002) proposes a distributed protocol for target tracking. They organized the sensor cluster and used triplet triangulation to predict the target's present location. The next position of the target identified using a linear predictor. The number of animal tracking system developed by researchers in the past years (Yang and Sikdar 2003; Zhang et al. 2004; Wark et al. 2007; GPS). Akbas et al. (POST) proposed a protocol for mobile object tracking. They experimented with gorilla equipped with sensor node while the Silverbacks equipped with actors.

Author in (https://www.sdmmag.com/articles/94763-ic-realtime-debuts-ai-powered-search-engine-for-security-surveillance-video) and (Senthil Selvi and Sukumar 2018) have discussed about a security technology named Ella, is a deep learning method as a search engine used in cloud-based surveillance applications to analyse recorded video [illegible]. The search engine augments the surveillance system using the searching capabilities obtained from natural language processing. Ella is a built-in application which cannot be used for all the applications, also it is not time efficient method. Pan et al. (2018) proposed an unnamed surveillance monitoring system, is a cost effective, consists of monitoring centre and measuring stations. It has a web service which uses a map, cameras, water level analyser and routers for measuring the level of water and determines the level of rivers and reservoirs in a web application. The communication router used to transmit the water level to the server through internet through a cellular network. This surveillance system used to intimate the flood disaster and provide prevention system. Most of the deep learning models used CNN for various applications in computer vision applications (Pereira et al. 2016). It is because of the great performance has been obtained by various applications using CNN. For example, image classification (Krizhevsky et al. 2012b), face recognition (Li et al. 2015), pedestrian detection (Zeng et al. 2013), and (Senthilselvi and Sukumar 2014) etc.

Chan et al. (2015), and (Selvi et al. 2019) proposed a very simple deep learning network for image classification which based on very basic data processing components. The proposed architecture PCA is used to learn multistage filter banks which is followed by simple binary hashing and block histograms for indexing and pooling. This architecture is called the PCANet. Two simple variations of PCANet named (1) RandNet and (2) LDANet were introduced to share the same topology as PCANet, but their cascaded filters are either randomly selected or learned from linear discriminant analysis.

Dragan et al. (2016) and Kryftis et al. (2017) proposed an opportunistic multimedia sharing algorithm for delivering multimedia content in opportunistic network. The proposed multimedia sharing algorithm is the extension of the author's previous algorithm named as Social PRediction based routing in opportunistic NeTworks (SPRINT) algorithm (Ciobanu et al. 2013). This algorithm has been implemented for supporting overlay for transferring media content over mobile-to-mobile very speedily. It uses wireless communication protocol for data transmission. It reduces the congestion and the success rate of data transmission is 80% where it needs to be improved. Kryftis et al. (2017) and Dragan et al. (2016), proposed a new multimedia service to deliver multimedia contents through resources selected based on optimal resource allocation model. The content delivery satisfies the user requests by exploiting the existing servers' capabilities. The proposed service is a proven model for demonstrating video-on-demand process.

From the survey, it is clear and noted that still the applications of WSN extended into various real-time environments and their efficiency should be given to the public. Also, it is considered that, this is the first application incorporating the application with environment.

4 Limitation and motivation

This paper focused on design and implements an efficient object tracking algorithm for animal tracking in thick forest. Among various real-world applications, animal monitoring in deep forest areas become an exciting and necessary application. From the literature survey, it is noted that most of the object tracking focused on monitoring and tracking objects in a fixed place, for a specific object, or looking for abundant object detection in a public place, etc. The sensors are fixed sensors, record the data and pass it to a server in the form of video. Some of the problems faced by the earlier research works are, nodes mislay their energy soon, since they restricted in their battery capacity. Monitoring the network region entirely and informing the server in a critical situation is also an essential requirement need in the surveillance monitoring. Some individual embedded applications have done it, but the cost of the circuit system is not cost effective. The significant problems taken into account here is, energy, implement a WSN application without changing the environmental information, analyze the monitoring data algorithmically and create an opportunity to explore an innovative area of wireless communication in real time environments.

The existing research works mainly used supervised learning algorithms from machine learning approaches. Most of the applications used machine learning and deep learning for object detection and classification. Objects are predefined as car, people or abundant objects. Also, machine learning algorithms are not fully automatic in feature extraction, The classification accuracy needs to be improved.

This paper motivated to design and implement a novel deep learning framework for identifying and broadcasting abnormal event by learning the surveillance data and broadcast it to apply immediate action. Each abnormal data is identified by learning the odd events occur in the objects (living things in forest environment).

Hence this paper motivated to design and implement a novel deep learning framework for identifying and broadcasting abnormal event and create a multi-path for routing the data. This paper absorbed in monitoring wildlife to know their doings, food, growth and their locality. If any new baby animal, forest officers can help them, provide food, water and if any animal dead, close their dead body properly to avoid infections on other animals. The proposed NDLF used deep convolution neural network for learning the video data. dCNN not only learn the data, it also extracts the features and classify automatically. The image data is moving objects, which are segmented automatically and classify them based on their activities. Objects are the foreground images placed on a background. It is not assured that the background images are static. If the background image is changed frequently, then detecting and classifying the foreground objects is difficult.

5 Existing research work

In the existing system (Hsu et al. 2012) the author considered energy is the primary factor. To provide an energy efficient routing, the author proposed a short-term Prediction based Optimistic Object Tracking Strategy (POOT) which increases the network lifetime by saving energy in individual sensor nodes. The sensor nodes used for object tracking based on time, cost and communication effectiveness. During the Object tracking, the routing distance is minimized by collecting the location information. The communication time taken for object tracking is reduced, using face model. POOT did not speak about the direction. Hence it needs to deploy many sensor nodes, and the volume of the data collection is increased time to time. Naturally, it improves the data comparison time and more memory. Also, POOT did not discuss about direction and angle of the sensor nodes which will also increase the number of nodes deployed the network. This paper proposed NDLF method, to overcome these kinds of problems which restricts the number of nodes, make the sensors as rotatable, and the sensing angles are determined so that the monitoring information increased. Past 5 years various numerical, theoretical and simulation-based applications made on object tracking. From an in-depth study applied to the earlier research works, it came to understand that all the reviews are highly general and discussed node deployment and location tracking process. The primary objective of this research work is to design and implement a novel approach for tracking animals in thick forests. The significant issues focused in this paper are, identifying specific Good/Bad activities and apply remedy immediately. Also, this paper focused on improving the network lifetime by controlling the node activities based on time. This paper focused on multi-object tracking and identifying the events. NDLF approach is proposed to do that, and it is implemented and compared with TORS and CORS for performance evaluation.

6 NDLF system model

The forest environment considered as a network G, which has been deployed fully with N number of wireless sensor nodes. Sensor nodes are the highly active remote cameras, adjustable and rotate by itself slowly within a defined angle [illegible]

$$G = \left\{ G_1, G_2, \ldots, G_i, \ldots, G_M \right\}, \forall i \varepsilon 1 \text{ to } M// \quad \text{M number of forest networks} \tag{1}$$

$$G_i = \left\{ N_1, N_2, \ldots, N_j, \ldots, N_N \right\}, \forall j \varepsilon 1 \text{ to } N// \text{ N number of nodes} \tag{2}$$

Multiple objects are considered as objects to track their activities. It is assumed and implemented that the objects are static as well as moving objects. All the objects walk in a forest network which divided into quadrants of the equal angle of (90°). Each object is tracked based on their locations in a two-dimensional network (Fig. 2).

7 Node deployment

Network G considered as a circular shape, and the nodes are deployed randomly and distributed within the region X and Y. X is the maximum width and Y is the maximum height of the network. Hence any node can be placed anywhere within X and Y and the all the nodes are moving (not always). Nodes can move in any direction from 0° to 360° in the network. Monitoring and recording a moving object within a distance or at an angle is easy, and most of the earlier research works do it. But, here, the surveillance system is focused on monitoring the objects within a region and the objects are also multiple. During the node deployment process, all the nodes information

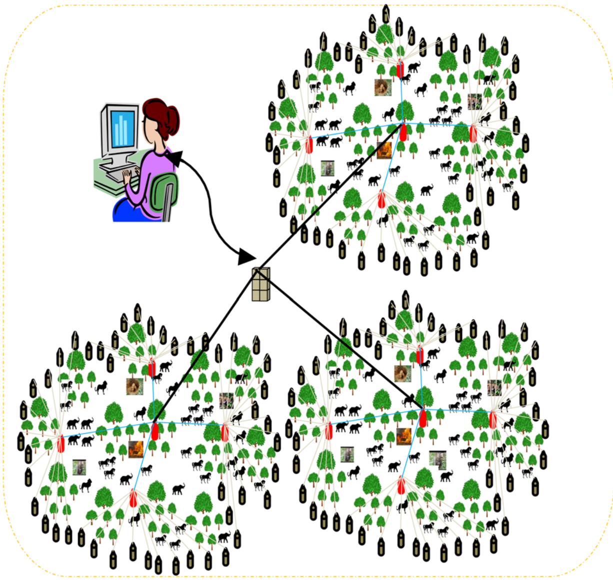

Fig. 2 NDLF network model

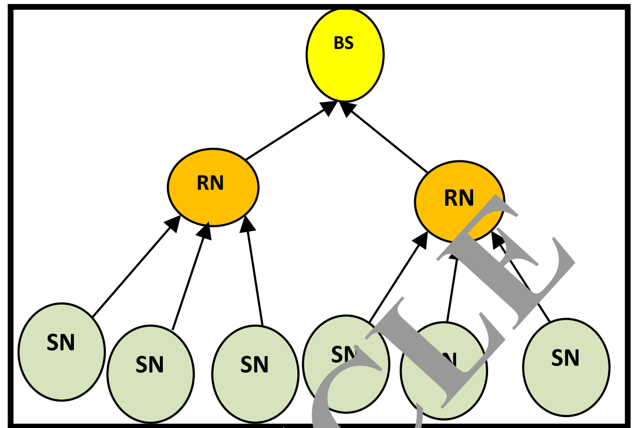

Fig. 3 Functional architecture

such as node-number, node name, deployed location, current location, and comments about the nodes' last activities stored in the Node-database.

Whenever the admin detected a new activity from the monitoring data, the activity updated as a comment in the last column of the Table 1. Once the nodes deployed, they activated in the network, and they start monitoring the process in the network. It is assumed that the network shape is considered circular and divided into four quadrants. *N* nodes with five relay nodes (*RN*) deployed in the network (see Fig. 3). The *N* nodes deployed around the circle and the five *RN* nodes deployed within the quadrants. The RN nodes are acting as normal monitoring node as well as relay node. During the relay, the data from all its sensor nodes reproduced without any data loss. The sensing angle and time to complete one round of operation should satisfy the following equality and inequality constraints as:

$$0 \le I\theta \le \theta \le F\theta \le 360 \tag{3}$$

$$t_s \le t \le t_e \tag{4}$$

$$N = \{N_1, N_2, \ldots, N_i, \ldots, N_N\} \tag{5}$$

The entire nodes are categorized into two classes such as odd-numbered and even-numbered nodes, and they represented as:

$$ON = \{N_1, N_3, N_5, \ldots, N_{N-1}\} \tag{6}$$

$$EN = \{N_0, N_2, N_4, \ldots, N_N\} \tag{7}$$

The other way of considering the network architecture is tree-architecture. The number of RN and SN is unlimited. This paper, NDLF connects many forest networks G_i by interconnecting the RN with the BS directly. If necessary, that is, if the distance from an RN to BS is high, then that RN can connect to BS with the help of another RN in the network. The physical structure of the SN, RN and BS connection resembles the LEACH protocol. The logical functionalities of the entire forest network are applied based on tree-architecture. All the sensor nodes monitor, record, and transmit to the RN available within the quadrant. Then RN nodes send the data to the base station. From the base

Table 1 Node-table

Node-number	Node-name	Deployed location	Present location	Comments
N001	Elephant	320,123	456,378	Nil
N002	Lion	121,548	382, 342	Nil
N003	Horse	100,231	145,289	New baby
:	:	:	:	:
:	:	:	:	:
N00N	Deer	385,457	482,489	Fire accident

station, the admin of the network can investigate and identify the activities of the network. Based on events the manual applications are executed.

8 Observing objects in forest network

The monitoring process of the sensor node is carried out in two steps. One is in the anti-clock direction of monitoring calculated in $+\theta$, and the other is in the clockwise direction in $-\theta$. Each sensor changed their angle from an $I\theta$ to $F\theta$ within a time interval, and it is shown in Fig. 4a. Once the node reached the final angle $F\theta$, it reset its values, final as initial and initial as final and it rotates clockwise, and it is shown in Fig. 4b.

The sensor nodes changed their θ, from $I\theta$ to $F\theta$ within a time intervals. It can be represented by:

$$\mathrm{F}\theta \leftarrow \mathrm{I}\theta \tag{8}$$

$$\mathrm{t_{st}} \leftarrow \mathrm{t_{et}} \tag{9}$$

And repeat the process of rotating and monitoring the environment as shown in Fig. 4.

Also, the nodes that are classified into ON and EN do the monitoring process by Sleep/activate method. When the ONs are in sleep mode, then the ENs has inactivated the mode. Reversely, when the ENs is in sleep mode, then the ONs are inactivating the mode. It reduces the complexity, saves memory and mainly it reduces the energy consumption and prolongs the network lifetime.

The logical functionality of the proposed system is illustrated in Fig. 5. A portion of the system monitors the environment and records the data. The recorded data is directly

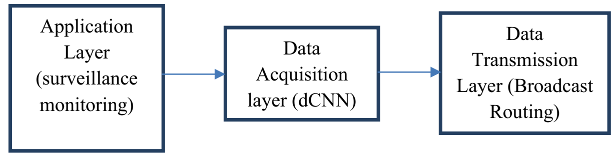

Fig. 5 Logical diagram of the proposed system

feed into data acquisition process using dCNN. Finally, the layer provides the classified output as normal or abnormal. If abnormal classification label is found then, the abnormal alert and the corresponding input is directed to the router. The router broadcasts the abnormal message.

The functionality of dCNN is illustrated in Fig. 6. The proposed dCNN model is illustrated in Fig. 6, it has 2-convolution layers, 2-pooling layers and 1-fully connected layer. Initially for the activation of convolution layer the Rectifier Linear Unit is used as a function. The convolution and pooling layers learn the entire data repeatedly in terms of features and the hidden information of the input data. From the input data the objects are selected as $\mathbf{m} \times \mathbf{n}$ pixels (depends on the object size) with RGB as a sample for learning. While learning process the parameters of the CNN are tuned for obtaining the best set of parameters to increase the accuracy of object learning. After completion of learning process the labeling process is done by CNN. 40% of the data is taken for training process and the remaining is taken for testing process from the overall dataset. In both training and testing process the sliding-moving window is used to accurate object detection for learning process. For the classification of the abnormal objects some of the predefined images are also used. After successful learning process each object are labeled with

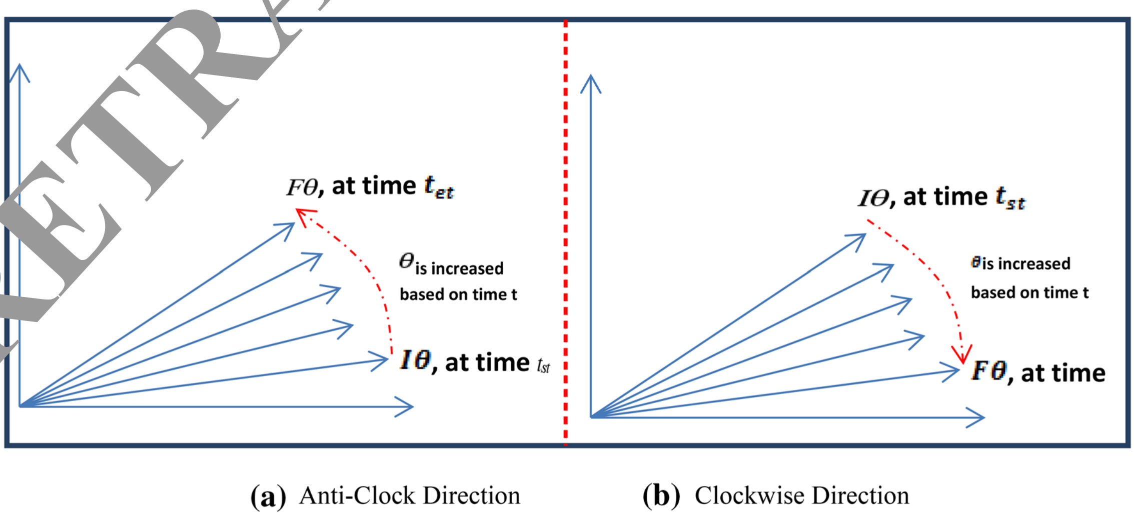

Fig. 4 Sensor node monitoring directions clockwise/anti-clockwise

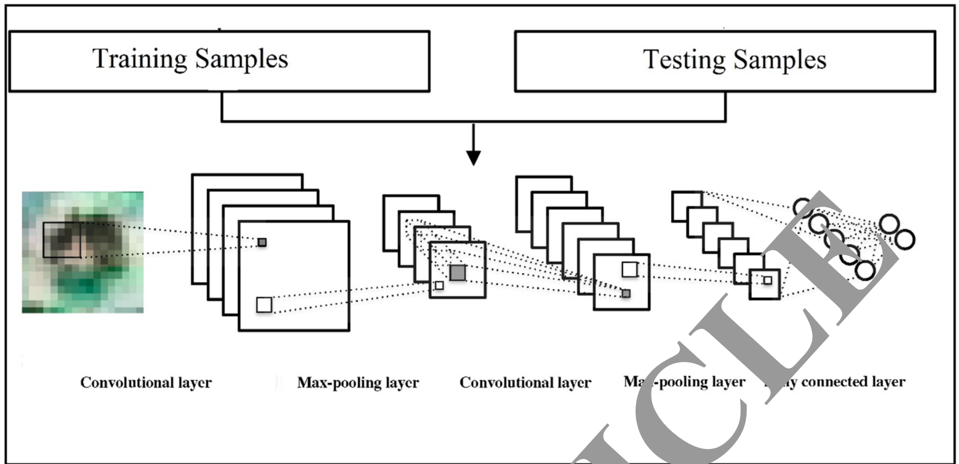

Fig. 6 dCNN based surveillance data analysis

normal or abnormal. During the testing process the same training process is applied on the input data and the CNN parameters are compared with the trained labels for predicting testing class effectively and speedily.

9 dCNN based data manipulation

The real process of NDLF is data manipulation, which learn the video frames, extract the features and classify the objects as normal or abnormal. The whole video is not continuously applied for processing in NDLF. The video is divided into small segments with length of 50 frames only and it applied for processing, where it can be processed speedily and effectively. Initially the foreground is separated from the background and the foreground objects detected by a tight bounding box. Bounding box is created over the objects using Region of Interest (ROI) method. By using prior knowledge, the normal abnormal images are classified in the existing approach (Ren et al. 2013). Another existing method used Bag of Visual Words model for object classification (Blei et al. 2003; Fei-Fei and Perona 2005). But the time complexity and comparison complexity are high. The algorithms used in (Ren et al. 2013; Blei et al. 2003; Fei-Fei and Perona 2005), has their own merits and demerits. To solve the various issues and challenges faced by the existing approaches (Ren et al. 2013; Blei et al. 2003; Fei-Fei and Perona 2005), this paper used deep Convolutional Neural Networks (dCNN) algorithm for video analysis. It is described that the dCNN method obtained a superior performance than several state-of-the-art image processing algorithms (Krizhevsky et al. 2012a; Kavukcuoglu et al. 2010; Large Scale Visual Recognition Challenge 2012), but they need high amount of trained data. In the proposed method 40% of the data is taken for training process. The dCNN model has 3 convolutional and max pooling layers. The kernel size of convolution layer is 9×9 and the pooling layer is 2×2. The entire layers are described in terms of input size, kernel size and output size are given in Fig. 7. The input layer size is 128×128 is applied to process in the convolution layer. The output of the convolution layer is 120×120 matrix with the 32 kernels. Because of 32 kernels, it provides 32 output matrixes, which has been feed into max-pooling layer represented by 2×2 block. The first level max-pooling layer provides $32 \times (60 \times 60)$ matrices as the output. This will be carried as the input to the second level convolution layer. In the second level a $64 \times (52 \times 52)$ matrix is produced by the convolution, feed into max-pooling layer and get the output of $64 \times (26 \times 26)$ matrix, is the output of the second level max-pooling layer and feed as input to the third level convolution layer. Finally, the output obtained from the third level max-pooling layer is $32 \times (9 \times 9)$ matrices, which will be converted into 2592-dimensional vector.

In the fourth layer a fully connected layer with SoftMax layer is involved in the dCNN architecture. The SoftMax layer has 20 neurons used for determining the input image as normal or abnormal. Final classification can be done by data augmentation method proposed in (Zeng et al. 2013) is followed here for training the dataset. In order to identify the normal and abnormal activities some of the images extracted from the input video is given in Fig. 8.

To identify the activities of the animals from the recorded video, the entire procedure on this NDLF approach is given in the form of algorithm, which is given below. The algorithm describes the node deployment, initializing the properties of SN, record the data, process the data and identify the activities are normal or abnormal by comparing the detection objects with the ground truth objects stored in the DB. The admin can select any video from at any sensor node in the network and can monitor the activities dynamically or taken from the DB which stored in the high capacity memory. The memory can manage by copying the oldest data into secondary memory to

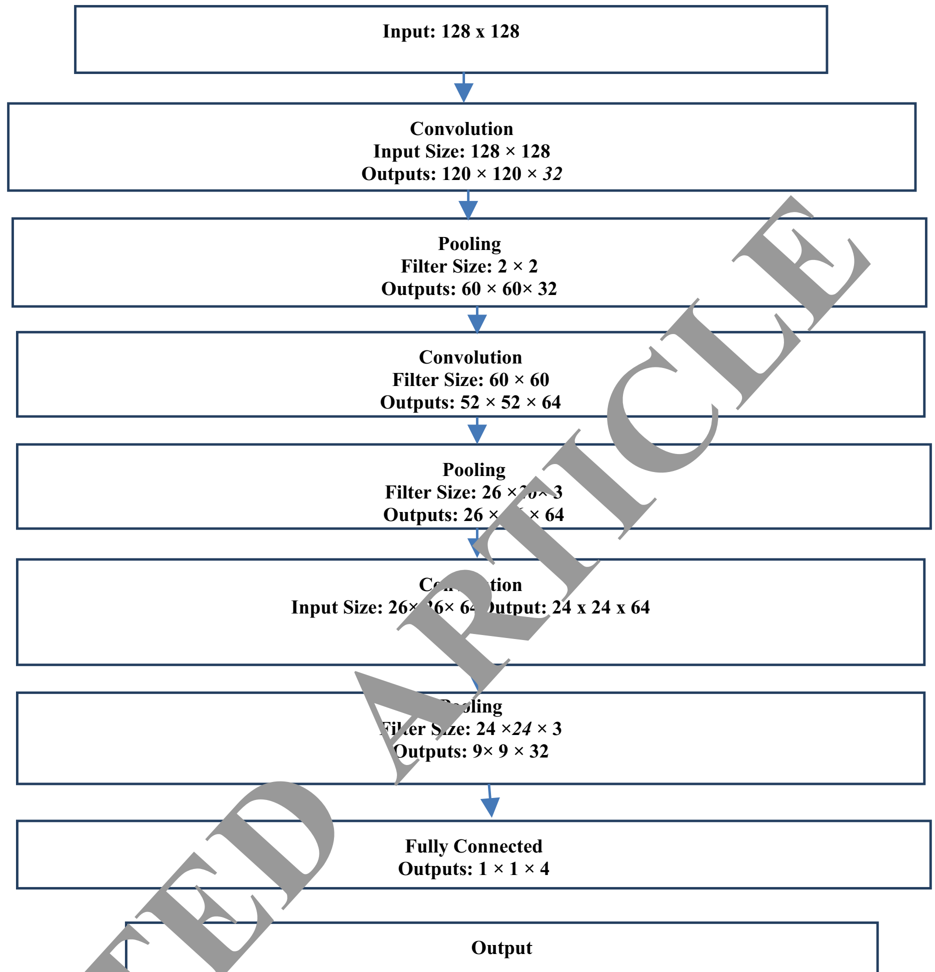

Fig. 7 Architecture of the proposed dCNN

Fig. 8 Normal and abnormal activities stored in ground truth images

control the memory regarding the speed. When the memory size filled with lesser data, then the speed of the NDLF is increased in animal activity detection. The efficiency of the proposed NDLF is verified by implementing the entire process in MALTAB software. One is for analyzing the effectiveness of the NDLF process in real time, and the other is to simulate the functionalities of the network behavior.

10 Simulation results and discussion

Number of SN, the area of the network, number of RN, θ and other necessary parameters are initialized in MATLAB software and executed; also, the recorded video is using a surveillance camera taken as an input and performed. The footage is divided into segments, and the segments are converted into frames then frames are applied using image processing methods for object detection and identification. The numbers of surveillance cameras are considered as sensor nodes which simulate the network functionality. From both experimental and simulation, the results are verified to understand the object tracking applications under WSN, and it helps to implement real-time applications.

The video played, and the optical flow analyzed. Then, on each frame background, subtraction and morphological operations are applied sequentially to detect the objects. After object detection, all the objects are compared with the ground truth scenes to identify the abnormal activities happen inside the forest. Once the event is detected manual protection is applied immediately on the spot. Some of the normal and abnormal activities identified by the proposed implementation are given in the following Fig. 9, whereas this kind of results obtained in real time applications deployed in any remote environments which are useful.

According to the above discussion and under various conditions, the proposed approach is programmed and executed in MATLAB software. The dataset used in the experiment collected from Wildlife Television. It is assumed that the initial process of the proposed method is noise removal on the frames which increases the video quality. Figure 9 shows the results obtained regarding normal and abnormal activities of the animal objects in the forest network. This unusual activity detection obtained by comparing with the ground truth images. A child elephant fell inside water, lion arresting an elephant, more lions are arresting a group of elephants are the abnormal activities obtained from the videos, and it results from the experiment.

Time complexity is the primary concern to be considered in object tracking where it degrades the performance. It should be noticed by the admin speedily to provide an immediate action against abnormal activities. As soon as the monitored data is transmitted to the admin, the remedy is applied. If any delay in the transmission and object tracking, there is no use of tracking in forest network. So that the playing time, object detection time should reduce. It is calculated in the experiment and makes the algorithm as efficient regarding video processing and image processing in the admin system. The time taken for splitting a video into the segment, segments into frames, frames into objects then identifying the object as normal or abnormal is calculated in the experiment and shown in Fig. 10. From the consequences, it is perceived

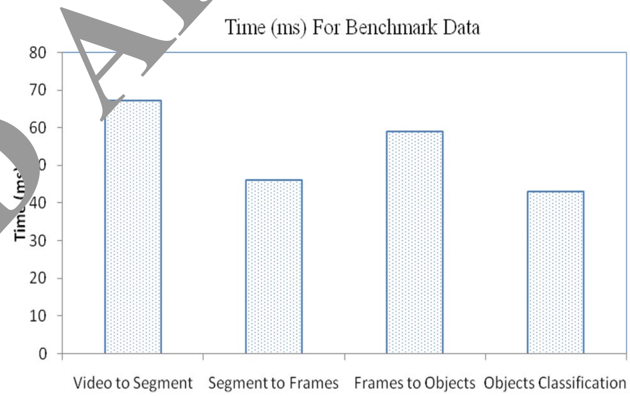

Fig. 10 Time complexity analysis for benchmark data

Fig. 9 Normal and abnormal activities detected using object tracking in WSN

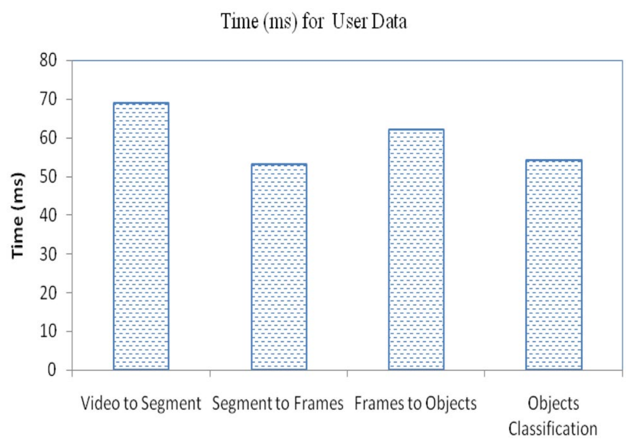

Fig. 11 Time complexity analysis for user defined data

that the video into segment processing time is more than the other processes. The object identification time is lesser than the different timings comparatively where it increases the performance of the proposed approach. Also, the time complexity is verified based on the data.

The experiment is carried out using benchmark data and user-defined data. User-defined data is, the user record a video data in the forest network using their handy camera. The time complexity comparison is shown in Fig. 11. The time taken for data process is merely equal to both the data, hence it is identified that the proposed approach supports any data. The lesser time reduces the cost, and it satisfies the customer.

In Fig. 12, N number of sensor nodes (SN) and a number of relay nodes (RN) are deployed in the network, in which location of each sensor node (SN) is randomly chosen as (xi, yi). Since the nodes are rotating nodes, they rotate in both clockwise and anti-clock wise at angle theta (θ). The rotation time and monitoring time (t) is calculated from 0 to T. Each time the starting time ts and the ending time te are calculated, which is used to check whether the interval is correct or not. The recorded data by the ith sensor node SN(i) is stored as a video V(i). The video is divided into

Fig. 12 NDLF algorithm

Algorithm_NDLF () {

Input: Number of sensors, locations of the sensors, rotating angle, and data(s) extracted from the monitoring data. Store the set of all ground truth images for normal and abnormal condition is in DB.

Initialization:

for $i = 1$ *to* N

Place all the SN and RN in the network // like in Figure-1.

$location(SN) = (x_i, y_i)$

$\theta = -\theta \text{ to } +\theta$ // it varies depending on the nodes

$t = 0;$

$t_s = 0, t_e = 0;$

end i

Monitoring Data:

for $i = 1$ *to* N

$V(i) = SN(i).data$

$Sg(i) = fr(i)$

end i

for $i = 1$ *to* N

$fr(i)$

fr(i) -> CNN-layer()

Feature(i) <- feature.fr(i)

if (feature(i) is matched with abnormal object feature) then =
"Broadcast " + alarm

else

End i

}

frames fr(i) and video segments sg(i) are created. From sg(i), the frames fr(i) are applied for object detection and identify whether the activity is normal or abnormal. Once the activity is identified as abnormal then alarm will be generated and the data is broadcasted.

From the experiment, the stage wise results obtained from the proposed NDLF is given in Fig. 13. The input image is given for preprocessing. Then preprocessing and feature selection is applied to the input image. Hence the image is identified whether normal or abnormal.

Generally, the image (frame) extracted from the video segment is stored as a JPEG image in a folder using MATLAB function. Each frame is RGB image, where it is not directly applied into CNN model. It is converted into grayscale and feed into CNN model. In the CNN model ReLU activate the CNN layers to intimate the image and its meta information. The convolutional layer and the pooling layers learn the images using m x n moving sliding window. Which learns all the information about the image and choose only the object information. The sliding window width, height and depth learns the features within the window and feed to fully connected layer. This layer predicts the existing classes according to the number of elements in the vector. The resultant vector has the classes of the input objects as normal or abnormal used for classification.

The error also influences the data processing in the data. A mistake in the video may be in frame level or the pixel level. Error occurs in the data due to noises created by multi-hop transmission, air, rain, windstorm and another natural resource, defect in the sensor node and others. The noise affects the entire frame or the pixels in the images. The noise may or may not be eliminated in the image. The error degrades the performance of the object tracking. Hence error analysis is identified from the experiment and the results given in Fig. 14 and Table 2. The error analysis is also compared with the existing approaches presented in Saligrama et al. (2017), Reddy et al. (2011) and Bertini et al. (2012). It is identified that the proposed NDLF model obtained less error in the frame as well as in pixel level of the monitored data by comparing with all the methods. Table 4 shows the error level comparison of benchmark and customer-defined dataset.

During the classification, the true positive rate (TPR) and false positive rate (FPR) calculated over benchmark and customer dataset. TPR and FPR determine the accuracy of the classification of the NDLF approach. Both TPR

Table 2 Comparison of error analysis in various datasets

Methods	Err (frame level) (%)	Err (pixel level) (%)
NDLF model (benchmark DS)	8	11
NDLF model (custom DS)	11	17

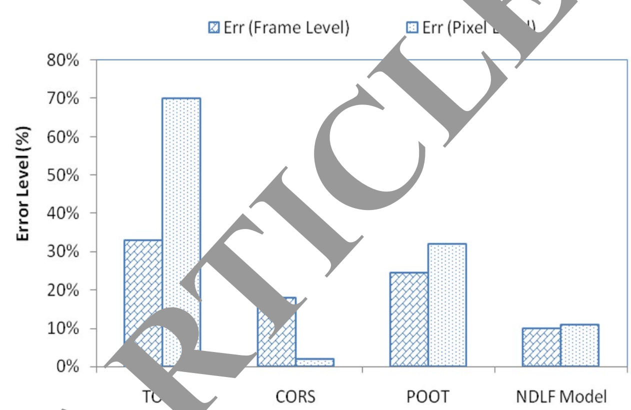

Fig. 14 Error analysis in frame and pixel levels

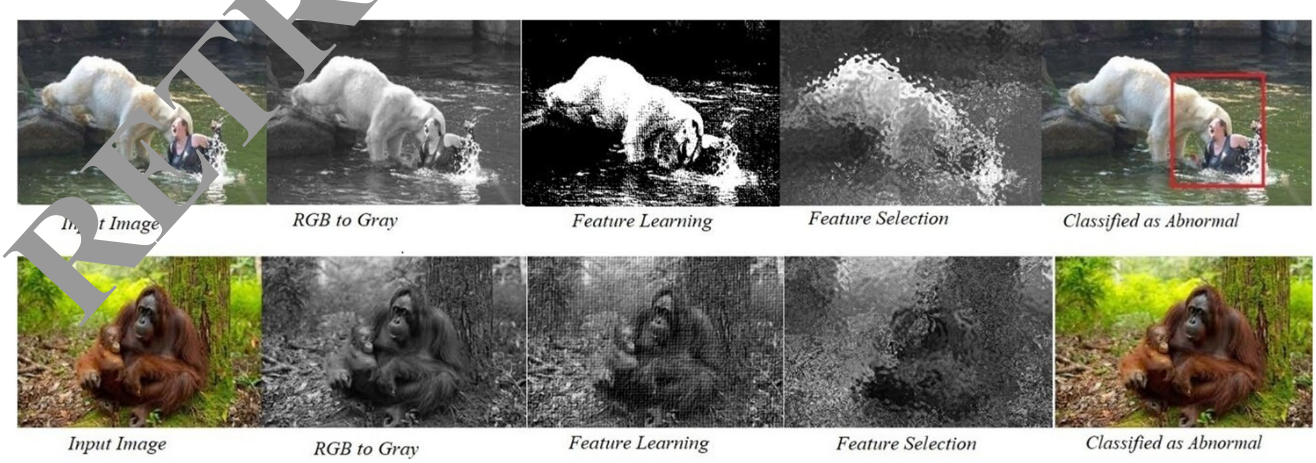

Fig. 13 Stage wise result obtained using NDLF

Fig. 15 Comparison of false positive rate versus true positive rate for UCSD-AD DS

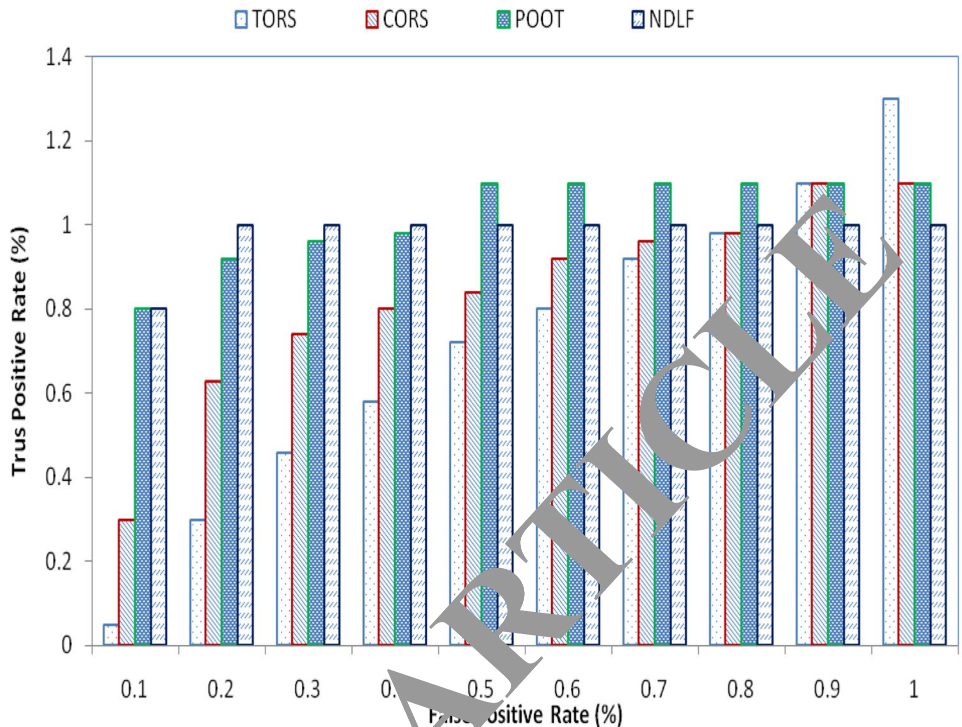

Table 3 Performance analysis based on sensitivity and specificity

NDLF model (benchmark DS)	NDLF model (custom DS)
0.18	0.07
0.32	0.13
0.47	[illegible]
0.61	0.41

Table 4 Performance analysis for NDLFon various datasets

	Correctly classified (number of frames)				
Dataset	200	400	600	800	1000
NDLF model (benchmark DS)	200	400	598	798	997
NDLF Model (custom DS)	195	389	591	783	981
	In correctly classified				
Dataset	200	400	600	800	1000
NDLF model (benchmark DS)	0	0	2	2	3
NDLF model (custom DS)	5	11	9	17	19

and FPR estimated from the experiment, and the result is shown in Fig. 15. From the results, it is noticed that TPR obtained using NDLFis higher than the existing approaches. Also, the TPR is calculated and plotted in the graph against FPR. Similarly, the performance is calculated for benchmark dataset and custom designed dataset and verified. Sensitivity and specificity obtain it to the NDLF model. Similarly, Table 3 shows the performance of the NDLF model is better for both benchmark dataset as well as a custom dataset. Also, the performance evaluated by calculating the sensitivity and specificity using NDLF model.

The above Fig. 14 and Table 2 show the comparison between sensitivity and 1-specificity. Here, NDLF approach obtained better value than the other values for both datasets. In general, it is well known that for the same value of sensitivity the obtained specificity becomes poor. If the discussed processes are accurate, then the accuracy of the object tracking and identification is increased automatically. The efficiency obtained by calculating the correctly classified and not-correctly classified objects, and it is given in Table 4. It estimated from the experiment for the different dataset, and the results are verified. For the results and discussion, it is observed that the NDLF approach obtained 99.53% and 98.11% as correctly classified the normal and abnormal frames from benchmark dataset and custom dataset respectively. As well as, the incorrect classification percentage is 0.23% and 2.03% for normal and abnormal frames from benchmark dataset and custom dataset respectively, and it is given in Table 4.

The performance of the proposed NDLF the accuracy of objects detection and classification results is compared with the existing approach (Li et al. 2016) used for palm tree detection and classification using same CNN model. Some of the performance measures such as precision and recall are calculated and compared with the results obtained in (Li et al. 2016). The comparison result is given in Fig. 16.

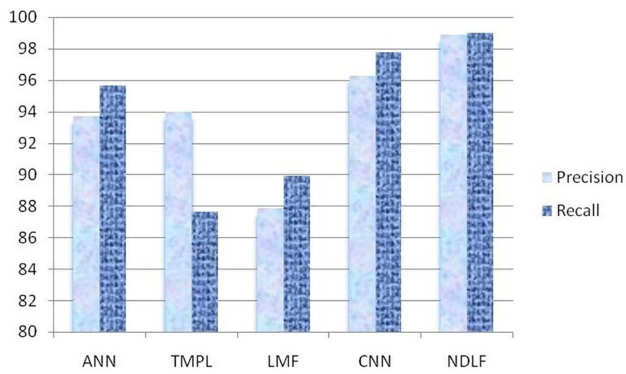

Fig. 16 Performance comparison

From the above discussion it is clear that this proposed a novel framework detect and classifies the abnormal activity happening in the surveillance environment. This paper integrates the application with the base environment/network where it comprises of surveillance application, video/image processing, and routing the data in WSN. It focused on three different process parallel such as video to image conversion, image processing, object detection and classification, and routing the abnormal data. Routing process route the normal data normally and broadcast the abnormal data due to save the environment. The experimental results present in this paper describes the image processing performance and networking performance. From the performance comparison, it is concluded that the proposed NDLF approach is a better approach for object tracking and it is suitable for any digital video regarding object tracking and object classification.

11 Limitation of NDLF

The limitation of the NDLF is, some difficulties are faced while integrating the surveillance application into the WSN. Also, application setup and initial execution takes more time.

12 Conclusion

The primary objective of this paper is to design and implement WSN application for surveillance monitoring in forest network. It is used to do object tracking and identifying activities of the objects as normal or abnormal. To do that a NDLF method with increased efficiency regarding energy and cost. The proposed NDLFhas been implemented, and experimental work has been one by using MATLAB software and the results are verified. To evaluate the performance obtained results using NDLF is compared with existing approaches a Time-efficient Object Recovery Scheme (TORS) and a Communication-efficient Object Recovery Scheme (CORS). The obtained results from the experiment are shown in the results and discussion section. From the results, it is identified and concluded that NDLF approach is better and suitable for online video processing when compared to other contemporary methods. In future, the same experiment is verified with various datasets and verifies the performance.

References

Bertini M, Del Bimbo A, Seidenari L (2012) Multi-scale and real-time non-parametric approach for anomaly detection and localization. Comput Vis Image Underst 116(3):320–329
Blei David M, Ng Andrew Y, Jordan Michael I (2003) Latent dirichlet allocation. J Mach Learn Res 3:993–1022
Chan TH, Jia K, Gao S, Lu J, Zeng Z, Ma Y (2015) PCANet: a simple deep learning baseline for image classification? IEEE Trans Image Process 24(12):5017–5032
Ciobanu RI, Dobre C, Cristea V (2013) Sprint: social prediction-based opportunistic routing. In: World of wireless, mobile and multimedia networks (WoWMoM), 2013 IEEE 14th international symposium and workshops on a. IEEE, 2013, pp 1–7
Dragan I (2016) Multimedia sharing over opportunistic networks. In: 2016 IEEE 12th international conference on intelligent computer communication and processing (ICCP). IEEE, 2016
Fei-Fei L, Perona P (2005) A bayesian hierarchical model for learning natural scene categories. In: Proceedings of the 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)—Volume 2—Volume 02, Washington, DC, USA, 2005, CVPR'05, IEEE Computer Society, pp 524–531
Gossett S (2004) Spy chips' for nation's livestock?, WorldNetDaily.com, February 28, 2004
Guibas L (2002) Sensing, tracking, and reasoning with relations. IEEE Signal Process Mag 19(2):73–85
Hsu JM, Chen CC, Li CC (2012) POOT: an efficient object tracking strategy based on short-term optimistic predictions for face-structured sensor networks. Comput Math Appl 63(2):391–406
Juang P, Oki H, Wang Y, Martonosi M, Peh L, Rubenstein D (2002) Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with zebranet. SIGOPS Oper Syst Rev 36(5):96–107
Kavukcuoglu K, Sermanet P, Boureau YL, Gregor K, Mathieu M, LeCun Y (2010) Learning convolutional feature hierarchies for visual recognition. In: NIPS, 2010, pp 1090–1098
Krizhevsky A, Sutskever I, Hinton GE (2012a) Imagenet classification with deep convolutional neural networks. In: Bartlett P, Pereira FCN, Burges CJC, Bottou L, Weinberger KQ (eds) Advances in neural information processing systems, vol 25, pp 1106–1114. https://doi.org/10.1145/3065386
Krizhevsky A, Sutskever I, Hinton GE (2012b) ImageNet classification with deep convolutional neural networks. In: Proceedings of the advances in neural information processing systems, Lake Tahoe, NV, USA, 3–8 December 2012, pp 1097–1105
Kryftis Y et al (2017) Resource usage prediction models for optimal multimedia content provision. IEEE Syst J 11(4):2852–2863
Large Scale Visual Recognition Challenge 2012 (ILSVRC2012), http://www.image-net.org/challenges/LSVRC/2012/
Li H, Lin Z, Shen X, Brandt J, Hua G (2015) A convolutional neural network cascade for face detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition, Boston, MA, USA, 7–12 June 2015, pp 5325–5334

Li Weijia, Haohuan Fu, Le Yu, Cracknell Arthur (2016) Deep learning based oil palm tree detection and counting for high-resolution remote sensing images. Remote Sens 9(22):2–13. https://doi.org/10.3390/rs9010022

Liu JJ, Liu J, Reich J, Cheung P, Zhao F (2003) Distributed group management for track initiation and maintenance in target localization applications. In: Proc. of 2nd international workshop on information processing in sensor networks (IPSN'03), Palo Alto, CA, 2003

Mainwaring A, Polastre J, Szewcyk R, Culler D, Anderson J (2002) Wireless sensor networks for habitat monitoring. In: Proc. of the workshop on wireless sensor networks and applications, Atlanta, GA, 2002

Pan Jinqiu, Xiong Jian, Gui Guan (2018) Deep learning-based unmanned surveillance systems for observing water levels. IEEE Access 6:73561–73571. https://doi.org/10.1109/access.2018.2883702

Pereira S, Pinto A, Alves V, Silva CA (2016) Brain tumor segmentation using convolutional neural networks in MRI images. IEEE Trans Med Imaging 35(5):1240–1251

Reddy V, Sanderson C, Lovell BC (2011) Improved anomaly detection in crowded scenes via cell-based analysis of foreground speed, size and texture. In: CVPR 2011 workshops. IEEE, pp 55–61

Ren X, Han TX, He Z (2013) Ensemble video object cut in highly dynamic scenes. In: 2013 IEEE conference on computer vision and pattern recognition, pp 1947–1954

Saligrama Venkatesh, Zhang Ziming, Liu Yun, Chen Xi, Zhu Yanjun, Cheng Ming-Ming (2017) Sequential optimization for efficient high-quality object proposal generation. IEEE Trans Pattern Anal Mach Intell. https://doi.org/10.1109/TPAMI.2017.2707492

Selvi AS, Kumar KPM, Dhanasekeran S, Maheswari PU, Ramesh S, Pandi SS (2019) De-noising of images from salt and pepper noise using hybrid filter, fuzzy logic noise detector and genetic optimization algorithm (HFGOA). Multimed Tools Appl 78(14):1–17. https://doi.org/10.1007/s11042-019-7727-9

Senthilselvi A, Sukumar R (2014) A survey on image restoration technique. Int J Emerg Eng Res Technol 2(8):123–128

Senthil Selvi A, Sukumar R (2018) Removal of salt and pepper noise from images using hybrid filter (HF) and fuzzy logic noise detector (FLND). Concurr Comput Pract Exp 31(12):e4501

Shin J, Guibas L, Zhao F (2003) A distributed algorithm for managing multi-target identities in wireless ad-hoc sensor networks. In: Proc. of 2nd international workshop on information processing in sensor networks (IPSN'03), Palo Alto, CA, 2003

Wark T, Crossman C, Hu W et al (2007) The design and evaluation of a mobile sensor/actuator network for autonomous animal control. Proc IPSN 2007:206–215

GPS GSM lynx tracking in the Bavarian Forest National Park. http://www.environmental-studies.de/projects[illegible]/GPS-lynx-tracking/gps-lynx-tracking.html

POST—Pacific Ocean Shelf Tracking Project. http://postcoml.org/

Yang H, Sikdar B (2003) A protocol for tracking mobile targets using sensor networks. In: Proc. IEEE international workshop on sensor networks protocols and applications, Anchorage, AK, 2003, pp 71–81

Zeng X, Ouyang W, Wang X (2013) Multi-stage contextual deep learning for pedestrian detection. In: Proceedings of the IEEE international conference on computer vision, Sydney, Australia, 1–8 December 2013, pp 121–128

Zhang P, Sadler C, Lyon S, Martonosi M (2004) Hardware design experiences in ZebraNet. Proc SenSys 2004:227–238

Zhao F, Liu J, Liu J, Guibas L, Reich J (2003) Collaborative signal and information processing: an information directed approach. Proc IEEE 91(8):1199–1209

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