**Elephant Corridor for Movement and Identification Management Using Drone Camera in Deep Neural Network**

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**Abstract**

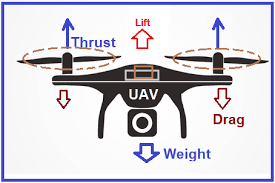
recently seat Chhattisgarh elephant human conflict is a major problem rabbit growth in the number that human and Elephant this major problem has resulted in a growing interest in conflict problems requiring solution this paper propose an Elephant corridor searching model that can extract discriminative feature through elephant for identification using a drone camera represent a robust baseline for how elephants can be identified using a drone camera the proposed elephant corridor identification network is a convolutional neural network CNN based network structure comparison all feature extraction and self-attention models more over there is no need for separate scanning of deforest movement in the elephant device because it use a popular drone camera pic to acquire the two type of data sets first elephant corridors and the second one is elephant movement beside high recognition performance the proposed drone camera searching method also ensure simplicity and efficiency the proposed to drone camera searching method achieves better recognition performance then estate of the art method for the collected elephant corridor detail and Elephant movement data set using multiple data set through cross-validation be acquired and average elephant identification accuracy of 98.59%.

**Keyword**

Elephant Corridor, Corridor Map, Drone Camera, Convolutional Neural Network (CNN), Deep Learning.

1. **Introduction**

Elephant corridor movement promising Chhattisgarh area of study with drone cameras for searching elephants in deep forests in the fields of vision of computer and deep learning in recent years. It extracting features discriminative by considering elephant corridor and elephant image processing trends, such as visual appearance, and three-dimensional view for, pattern recognition and Elephant corridor and movement **(H. S. Kuhl et al., 2013, & S. Kumar et al., 2018).** Accordingly, elephant corridor and movement have been applied systems in various Chhattisgarh forest areas for elephant corridor, and management analysis. the coexistence harmonious between people and elephants and major conflict and associated responsibility. Therefore, the elephant corridor and movements system is a drone camera for managing and elephant monitoring companion wild animals and elephants. The number of accident associated with elephant corridors and movement can be significantly minimized through drone camera monitoring for Elephant-Human conflict, tracking by elephants, and reducing poaching. Moreover, by enabling successful elephant pic as data and a corridor map is created for data can be collected from the Chhattisgarh forest to overcome the limitation imposed by insufficient elephant data set **(S. Kumar et al., 2018, 2017).**



**Fig. 1. Show Drone Camera Basic Features**

This work focuses on the efficiency improvement of the Chhattisgarh forest department for all elephant movements manage by drone cameras. while several reduce the elephant-human conflict sophisticated approaches are met in literature drone camera use search for an elephant corridor and its moments. today does not use in drone cameras for searching for the moment of the elephant in the Chhattisgarh forest. this happens mostly due to the elephant conflict that introduces drone camera monitoring for the elephant corridor and its movement. Step mandatory for our working drone camera monitoring methods which can have a great impact on their own coverage efficiency. Previous work can greatly impact Elephant identification and his identified behavior. but today's requirement is to minimize human-elephant conflict and knowledge of elephant movement. Our drone work is very impressive in minimizing elephant-human conflict in the Chhattisgarh forest. Fig. 1 shows the drones' basic features. Chhattisgarh elephant corridor is very big and not possible for only human searching. But our drone camera work minimizes the forest department problem.



**Fig. 2. Drone Camera**

1. **Size and Weight**

Now, drones our addressing range position frequency integration of all information technology communication technology robotization robotics hunting hurricanes, business operation disaster operation Timber Mapping Timber conservation guarding wildlife, and delivery parcels all work done by a drone camera. Two contribute to the development of an eco-efficient resource effective and competitive husbandry thought and enhanced and better use of drones and robotics. One important new task that drones are presently Bing assigned to is chart mapping. while looking every bit like an introduction model airplane that was designed only for recreational purposes I used it in my PhD work to collect data for photography by using mapping a camera in the fuselage with the help of came to a UAV. The Feather Light drones are now able to take thousands of digital images when serving geography. Each drawn of these images can also be collected to make complete and largely accurate 2D and 3D charts. Therefore, they suggest using the large drone for fixed-wing drones between 20 and 150 and multi-rotor drones between 25 and 100 kg small drones are fixed-wing drones up to 20 kg and multi-rotor drones up to 25 kg. within the category of small drones, they suggest using a subcategory of mini drones. Mini drones can size and weigh from grams up to approximate kilograms. Always mini drones are mainly used for indoor application and recreational applications. Examples of such drones are discussed later in this section.

1. **Types of Drones Used Our Works**

We have used five types of drone elements in our research work.

**3.1. Multi-Rotor Drone**

Multi-rotor drones are the very easiest and very cheapest option for getting these drones another name is “Eye-in-the-Sky” for our major work is elephant corridor and moment monitoring. they are also very effective in monitoring purposes and greater control offer over framing and position hence they are perfect for forest area photography of elephants and surveillance.

**3.2. Fixed-Wing Drones**

One type of rigid wings type drone. These drones are designed to be suitable for our work look and work like an airplane providing the lift rather than veridical lift routers. Hands This drone type is used to capture very fast and clear pick the photo and energy only needs to move forward and itself not to hold in the air. This makes long runs them energy efficient.



**Fig.3. fixed-wing drones show our universities students**

**3.3 single rooted drones**

Single-rotor drones are very stronger and high durable. they look like to actual mini helicopters in the structure and a design. A drone single rotor has just one’s router which is like one biggest spinning wing plus a tale router to control direction and stability.



**Fig. 4. Fixed-wing hybrid VTOL**

**3.4. fixed-wing hybrid VTOL**

The hybrid VTOL drone types benefits of beam fixed and designs rotor-based. This drone type has attached rotors to the fixed wings allowing it to hover and drone take off and map land verifiably. This category is new of hybrids is only a few on the technology advances in a market but as, this option can be very popular in the coming years. One example of a fixed hybrid bottle is Amazon prime year delivery drone.



**Fig. 5. Fixed-wings hybrid VTOL drones show our universities student.**

**3.5. Broadcasting Drones**

the use of drones provides broadcasters with an innovative way of capturing events the small and lightweight nature of the technology allows the media to get footage of the action like never before. ESPN tried drones at the x games in early 2015 as Fox used them indoors at the aim super cross series in March and again during the golf US Open both broadcast and camera technology are getting smaller and lighter the shooting platform also becomes more compact. What once required a chopper can now fit in small drones. So how can new technology like 5G and 8k video transform live broadcast.

**Fig. 6. Show the Broad Casting Drones**

**4. Related Work**

Out of the multitudinous great grounded CPP workshop, this section wave is named to present the sum of the most intriguing fairly recent bones. The workshop is presented in thrashing chronological order and the sum of the advantages and disadvantages of each work are stressed. The author **(L. nam et al., 2016)** propose an offline flight diary for a quadrangle rotor UAV that calculates contents circles to ensure qualitative data gathering for image mosaicking. the present result parts the workshop using approximate cellular corruption with the size of each cell determined by the UAVs detector reading and the task implication between two successional images, two Grace food processing of the data from image mosaicking. In **(C. A. Kapoutsis et al., 2017)** a grid-grounded methodology for multi-robot content path planning (MCPP) is presented. The crucial idea in this work is the multi-robot problem can be answered efficiently by dividing the overall ROI into exclusive sub-reasons equal to the number of robots that will be employed for the content procedure and also working a typical CPP problem for each sub-reason. This work uses the algorithm of the divided area of optimal multi-robot coverage path planning (DARP) algorithm introduced in the area allocation procedure. The gauging tree coverage **(Y. Gabriela et al., 2001)** (STC) algorithm is applied to all sub-reasons to induce the content path inside them. the methodology presented in the paper offers a small effective and safe result for the multi-robot problem wearing the possibility of cutting circles that can contribute to the development of more effective MCPP results for colorful operations.

**5. proposed system**

The proposed system for the Elephant corridor and movement monitoring for the Chhattisgarh forest has two main components. the first one is the drone searching all corridors and the second one is the monitoring elephant movement. these two components are very useful to reduce elephant conflict and the identification of individual elephants in the overall system flow of the processing system.

**5.1. automatic detecting in drone camera**

Elephants corridor and moment monitoring for Chhattisgarh forest the process flow of automatic detection and cropping of the elephant images. for detecting the elephant firstly, we perform the interface differencing between two consecutive frames of the elephants and corridor field image in order to detect the elephant. then we transfer the interface differencing result into the binary image by using the predefined threshold. the equation of interface differencing method based binary image creating is described in equation (1) 1 if threshold 0 otherwise

(1)

Where

Mt(x) is the result binary image of frame t,

It(x) is the cow’s image at frame t and

It – 1(x) is at the previous (t-1) frame

Then we use the white pixel occurrence (350 pixels) as a threshold in order to find the elephant corridor and movement monitoring. if the horizontal history count is greater or less than the threshold v regard that elephant corridor location as a pole location. if the elephant image and Elephant corridor are two poles location detected be used the corridor location which is located near the previously detected pole. for image cropping, we use the cropping height and weight by the fixed value of 450 pixels and 850 pixels respectively because the distance between the two poles' location and the length of the pole are the same for all frames. After getting the pole location we check it for finding the cropped image direction. if the value of the y corridor of the detection pole plus the image cropped height threshold of 450 is less than or equal to the height of the original corridor or elephant image then cropping is performed over the lower 450 pixels’ area of the elephant corridor and elephant images otherwise the upper 450 pixels are his cropped. Count the frequency of the occurrence of image pixels in the horizontal direction of each point along the vertical axis. As a result, we get the horizontal histogram of the binary image. The size of each frame is 1024x768.

**Fig. 7. 3D map in the forest**

The feature map is original obtained through the channel with the concatenated first step are then axis for corridor each map obtained through the reshaped image and attention channel module in the second step. the final I am waiting for vector is the attention model obtained through a fully connected (FC) layer. We used contrastive loss **(R. Headseel et al., 2006)** two optimize our model. The contrast you lost is calculate, check and apply the label of binary to appear positive negative elephant image and corridor image inputs. We also margin-based loss calculate and added additional **(J. Deng et al., 2019)** to extract the discriminative I am wedding vector of the elephant monitoring and corridor mapping CNN model. The loss is considered with the contrast your loss to optimize the elephant monitoring and corridor mapping CNN model. The experimental outcome indicates that the proposed elephant monitoring and corridor mapping CNN model framework superior reorganization illustrates performance to collected state-of-the-art methods for the elephant images data set. the contributions of our proposed elephant monitoring and corridor mapping CNN model framework r as follows

* The proposed elephant monitoring and corridor mapping CNN model method improves individual elephant corridor and Elephant movement managing systems perform through elephants based on techniques of Deep learning our method is the first step to identify an individual elephant based on Deep learning models. we provide a baseline robust model through the elephant monitoring and corridor mapping CNN model method for individual elephant identification systems.
* we ensure table and discriminative feature extraction by integrating the elephant monitoring and corridor mapping CNN model modules into and to and training and combined objective functions to optimize the elephant monitoring and corridor mapping CNN network.
* We experimentally demonstrate the superior performance of our collected elephant data set compared to state-of-the-art methods. we acquired an average elephant identification and Elephant corridor map creating an accuracy of 98.59% with the rank one approach.

**5.2. Deep Learning Feature-Based Methods**

Now a days deep learning for animal identification has become a key area of development in vision of computer technology. All approaches of are popular for image recognition image classification image detection and image tracking of objects for drone cameras therefore elephant images and Elephant corridor image identification recognition through deep learning. the elephant monitoring and corridor mapping CNN is popular for image identification by elephant monitoring and corridor mapping CNN deep learning architecture of that has outstanding demonstrated performance in various image computer vision tasks **(B. Shameem et al., 2021, K. He et al., 2016, Krizhevsky et al., 2012). (Hansen et al., 2018)** propose a day and animal identification system of the individual image that uses an Elephant monitoring and corridor mapping CNN model for training and testing with an artificially augmented data set from an unconstrained commercial form environment. **(Deb et al., 2018)** presented an animal face reorganization system called Prominent where a mobile application was used to directly obtained camera images of three primates in the wild: lemurs, golden monkeys, and chimpanzees. **(Hou et al., 2020)** used elephant monitoring and corridor mapping CNN with deep learning to propose a new individual identification system for the giant panda; they ensure the effectiveness and reliability of the panda image identification model by considering multiple treatments under various conditions such as panda large face angle low brightness and highest saturation. **(Wang et al., 2019)** used an elephant monitoring and corridor mapping CNN with residual learning to study the unique panda facial feature for gender classification. **(Kumar et al., 2018**) propose day and approach using individual deep learning architecture such as an elephant monitoring and corridor mapping CNN and deep network brief (DNB) for individual identification of cattle. The muzzle performance of print approach was superior to that of the feature-based approach by handcraft that was previously applied using image muzzle print. **(Favorskaya et al., 2019**) presented animal feature-based approach identification in wildlife based on mouth and shape features using a joint **(CNN. Hu et al., 2020)** proposed an Elephant identification system based on the features deep parts they use side view images of the elephant and corridor images to identify individual images.



**Fig. 8. Sample images of 13 elephants**

**6. Experiments**

We have discussed in this section the dataset and experiment setup

**6.1. Datasets**

In this study, we use the elephant forest some picture images and identify elephants and corridors. The elephant only can be used of biometric elephant authentication such as human iris patterns and fingerprints. This elephant and corridor also have the not changing over time is advantage. Therefore, elephant images are used to enable identification regardless of elephant images. However, because it is difficult to find or obtained elephant image data sets for the elephant image data set the data set is obtained directly. Several elephant rehabilitation and rescue centers were visited to collect elephant image data set each elephant was identified by its name. Therefore, there are no duplicate IDs in the elephant data set. The data set images were collected outside under sunlight or inside under a shed. The elephant image data set for collected using a drone camera extra scanning without equipment. This increases the elephant image convenience and elephant image efficiency data collection and processing using mobile devices. The images were taken with a resolution of 5032 pixels in the horizontal direction and 4024 pixels in the vertical direction and the elephant image areas were cropped automatically. only those elephant images with more than 640 pixels are selected for inclusion in the dataset of elephant images. Finally, 2561 elephant images from 13 elephants were collected for the data set.

**6.2. Experimental Setup**

We have to measure the points discussed in the section.

**6.2.1. Implementation Details**

In experiments our network where implemented using Python **(B. Shameem et al., 2022**). The experiments were conducted on a laptop computer with an Intel (R) core (TM) i5 CPU @ 3.20 GHz and 16.0 GB RAM. Before performing the image classification with the CNN module proposed method the collected elephant body part images data set input elephant images were resized to predict.

**Table 1. Confusion Matrix Scheme Prediction**

|  |  |  |  |
| --- | --- | --- | --- |
| Predict | | | |
|  | | Positive | Negative |
| Actual | Positive | TP (True Positive) | FN (False Negative) |
| Negative | FP (False Positive) | TN (True Negative) |

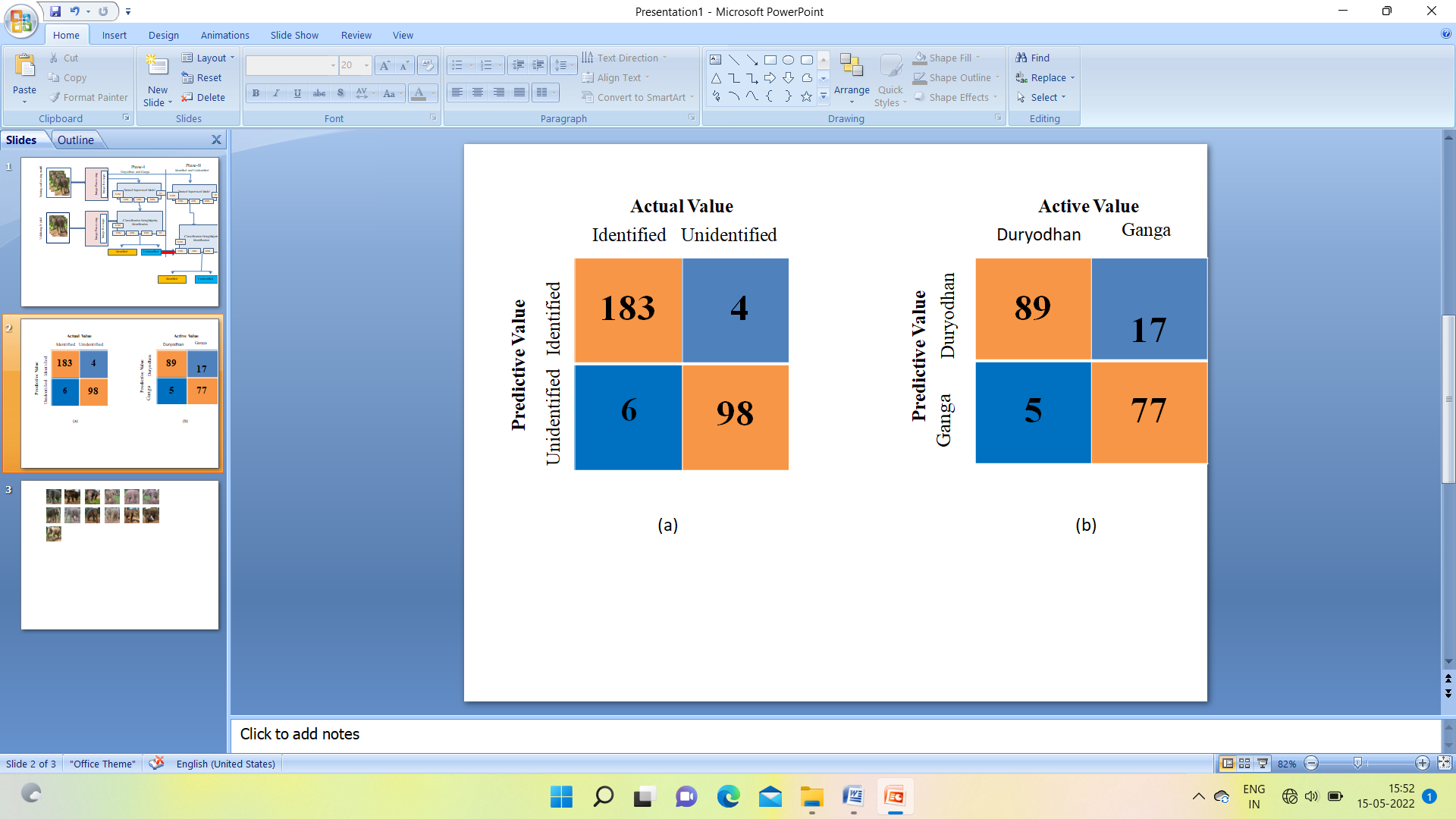
positive negative actual positive TP to positive FN (false negative) negative FP (first positive) TN (True negative) 256 x 256 pixels. The best size was used for 13 and the network was a trend for 23 epochs. Two objectives were simultaneously considered to optimize the network in an and to and manner. the fixed hyper parameter of contraception loss was m = 2. To optimize the proposed elephant monitoring and corridor mapping CNN sequential used the Adam **(B. Shameem et al., 2021)** optimizer with β1 =0.5 and β2= 0.999. furthermore, the hyper parameters s and m for loss wear are set to 30 and 0.5 respectively. We optimize the network module responsible for using the stockiest gradient descent (SGD) method where the momentum was 0.9 and the weight DK was 0.0005. the initial learning rate of 0.000 which was maintained over the first 100 epochs and linearly decayed to zero over the next 100 epochs. The embedding vector size used for future matching was set to 1024 dimensions.

-----------------------(2)

-----------------------------(3)

-----------------------------(4)

-----------------------------(5)



**Fig. 9. Confusion matrix Using the Validation Set**

**7. Conclusion**

This paper proposed an Elephant corridor and Elephant movement identified (CNN model) deep learning framework for individual elephant images. Our method identify is the first attempt to elephant image patterns for elephant different body part based on the learning models. The CNN model method aims to feature obtain robust and discriminative that can extract the unique patterns in elephant images. As ablation studies demonstrate the performance of combining objective functions for Elephant monitoring and corridor mapping optimization in CNN network with integrated modules that constitute elephant monitoring and mapping CNN model is more stable than using only part of the elephant monitoring and mapping model unable more stable and feature of discriminative extraction to identify features using the elephant body part images. Moreover, our experiment demonstrates that our proposed approach out performers state-of-the-art elephant monitoring and corridor mapping CNN methods on the collected elephant images data set. Consequently, the proposed elephant monitoring and corridor mapping CNN model can serve as a baseline repeat for individual elephant identification. In future work, we will discuss improvement in elephant identification and Elephant corridor monitoring by drone camera system by extending the elephant image data set. We also plan to obtain an elephant images data set for an additional wild animal such as a tiger leopard etc. As previously studies noted in related elephant images are important extraction feature that distinguishes mild species characteristics. Therefore, we will apply it to the task of identifying elephants. Elephant image and corridor movement identification using the rehabilitation differencing and horizontal histogram-based method for automatically detecting and cropping of the elephant and corridor map for training and recognition of the elephant image. We also create the elephant image data set of 13 different elephant images and perform experiments on that data set. The proposed system got an accuracy of 96.8% for automatically detecting and cropping elephants and corridor map reason and 97.01% for Elephant identification.

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