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Wild Animal Detection and Warning System Using Machine Learning and Deep Learning Algorithms

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Abstract
Animal detection and classification are crucial for the monitoring and preservation of wildlife. This project aims to develop a deep learning algorithm using Convolutional Neural Networks (CNN) to detect and categorize animals as either dangerous or non-dangerous in their natural habitat. As there are numerous animal species, manual identification can be a challenging task. The algorithm utilizes image classification to identify animals, which allows for efficient monitoring and prompt communication of safety concerns to the jungle supervisor. Animal detection and classification can help to safeguard people from animal-related hazards, prevent animal-vehicle accidents, track animals, and deter wildlife theft. Additionally, tourists can ensure their safety by avoiding dangerous animals or maintaining a safe distance while trucking in the forest. The successful implementation of deep learning techniques can lead to achieving this goal.

Keywords: CNN, machine learning, deep learning algorithms.

1. INTRODUCTION

Biodiversity is a vital feature of our planet, but the world's biodiversity is facing a high risk of decline due to various factors. Many organizations are working to improve the situation using new technologies such as machine learning (ML) and deep learning (DL). ML and DL have the potential to help in the identification and preservation of endangered species.

Machine learning refers to a branch of artificial intelligence that allows computer systems to enhance their performance through experience, without the need for explicit programming [1]. The goal is to allow computers to train themselves without human intervention and make better decisions in the future. Deep neural networks, including convolutional neural networks (CNNs), have been particularly successful in visual image analysis [2]. CNNs require relatively minimal preprocessing and can learn from data without prior knowledge or human intervention in feature design. CNN is used in various fields and its results are promising in accuracy.

Problem Statement

Monitoring wild animals in their natural habitats is critical for maintaining ecosystem health. However, increasing human populations and economic development have led to the excessive exploitation of natural resources and significant changes in the Earth's ecosystems. Human activities have also altered natural wildlife populations, habitats, and behaviors [3]. Many species have become endangered or extinct, and others have been displaced to new areas, causing disruptions to both natural and human resources.

Convolutional Neural Network

Convolutional Neural Networks (CNNs) have shown remarkable effectiveness in image recognition and classification tasks [4]. They have been used to identify various objects, animals, faces, traffic signs, and even power vision in robots and self-driving cars. CNNs have proven to be powerful tools for image recognition and classification tasks due to their ability to capture complex patterns and features in images.

A convolutional neural network (CNN) is a specific type of deep learning neural network that is intended for processing and analyzing data that has a grid-like structure, such as images or time series data. CNN leverages convolutional layers to discover patterns and features in the data [5]. The convolutional layer is the backbone of the CNN, as it extracts these features from the input image. Multiple convolutional layers are stacked on top of one another in the CNN, with each layer capable of recognizing increasingly complex structures. This architecture enables CNN to excel at the image and pattern recognition tasks.

ReLU and SoftMax are important components of a CNN that help introduce non-linearity into the network and make accurate predictions on image classification tasks Rectified Linear Unit (ReLU) is an activation function utilized in neural networks, which sets any negative values to zero and passes positive values through unchanged. It is frequently used to introduce non-linearity in the neural network [6]. SoftMax is an activation function that converts a vector of real numbers into a probability distribution over the classes in a multiclass classification problem, commonly used in the output layer of neural networks.

The CNN is structured with three primary layers, which are the input layer, the convolutional layer, the pooling layer, and the fully connected layer.

A. Convolutional Layer

The convolutional layer is a fundamental component of deep learning models used in various fields, including computer vision tasks such as animal tracking. This layer extracts features from input images by convolving them with filters that detect patterns such as edges, corners, and textures [7]. These features are used to train models that can track the animal in subsequent frames based on its past behavior. The convolutional layer preserves the association between pixels by analyzing small squares of input data, allowing for operations like edge detection, blur, and sharpening of images. The convolutional layer generates a feature map that identifies significant areas within the input image, which can be utilized for precise animal tracking.

B. Pooling

The pooling layer is a key component in convolutional neural networks that can effectively reduce the spatial dimensions of the input while retaining its significant features. Among various types of pooling layers, max pooling is widely used to shrink the input size by selecting the highest value within a local neighborhood [8]. The primary purpose of max pooling is to downsample the input image and decrease its dimensions, which can be beneficial for preventing overfitting and increasing the network's efficiency. In addition to reducing parameters, the pooling layer can accelerate the training process and enhance the network's overall performance.

C. Flattening

The flattening layer is responsible for transforming multi-dimensional arrays into a single linear vector. [9] It achieves this by breaking down the spatial structure of the data and converting the multi-dimensional tensor into a one-dimensional tensor, or vector [10]. By extracting and highlighting relevant features in the input data, the complexity of the data is reduced, allowing the neural network to analyze and process the data more effectively.

D. Fully connected layers

Fully connected layers, also known as dense layers, are a crucial component of Convolutional Neural Networks (CNNs). These layers are responsible for combining the learned features from earlier layers and creating a set of attributes that are then used to predict the output.[11] In a CNN, fully connected layers are typically added after the convolutional and pooling layers to create a more abstract representation of the input that can predict the outputs more accurately [12].They are a necessary component of CNNs and are responsible for much of their success in image recognition and other tasks.

2. PROPOSED RESEARCH METHODOLOGY

Stage:1 Data Collection - The first step for animal detection and classification is to collect an appropriate dataset. The dataset that contains images of animals that are to be identified and classified is collected from online resources like flicker.com and Kaggle.com. The dataset contains 14648 images of different types of animals and variations in lighting, background, and angle.

Stage:2 Pre-processing: Before we use the dataset for training our deep learning algorithm, we need to pre-process the images. This pre-processing step includes resizing the images to a common size, converting the images to grayscale or RGB, normalizing the pixel values to a common range, and augmenting the dataset by applying transformations such as rotation, cropping, and flipping [13].
We use the image dataset_from_directory () function from TensorFlow's Keras API to load the images from the directories into the training and validation datasets. The images are resized to a resolution of 128 x 128 pixels and normalized by subtracting the mean and dividing by the standard deviation. Additionally, the class names are extracted from the image labels and then associated with their corresponding categories of "Dangerous" or "Non-Dangerous".

Stage:3 Deep Learning Algorithm: For animal detection and classification, we use a deep learning algorithm Convolutional Neural Networks (CNNs). We use a convolutional neural network (CNN) model with several layers of convolutional and pooling operations, followed by fully connected layers with dropout regularization, and a softmax output layer. The CNN model uses the Keras Sequential API and includes the following layers:

A. Normalization layer: The input image is normalized by subtracting its mean and dividing it by its standard deviation.

B. Conv2D layers: The convolution operation is carried out using a specified number of filters (8, 16, 32, 64, 128) and a kernel size of 3x3, with the padding set to 'same'. This implies that zeros are padded to the input image to produce an output feature map that has the same spatial dimensions as the input.[14] The resulting output is then subject to the ReLU activation function.

C. MaxPool2D layers: Apply max pooling operation with a pool size of (2,2) to reduce the spatial dimensions of the output feature map.

D. Dropout layers: Apply dropout regularization to prevent overfitting.

E. Flatten layer: The output from the convolutional layers is transformed into a 1D vector by flattening it.
F. Dense layers: Apply fully connected layers with a specified number of units and activation functions. The last dense layer has the same number of units as the number of classes in the dataset.

G. Softmax layer: Apply a softmax activation function to the output of the last dense layer to obtain the probability distribution over the classes.

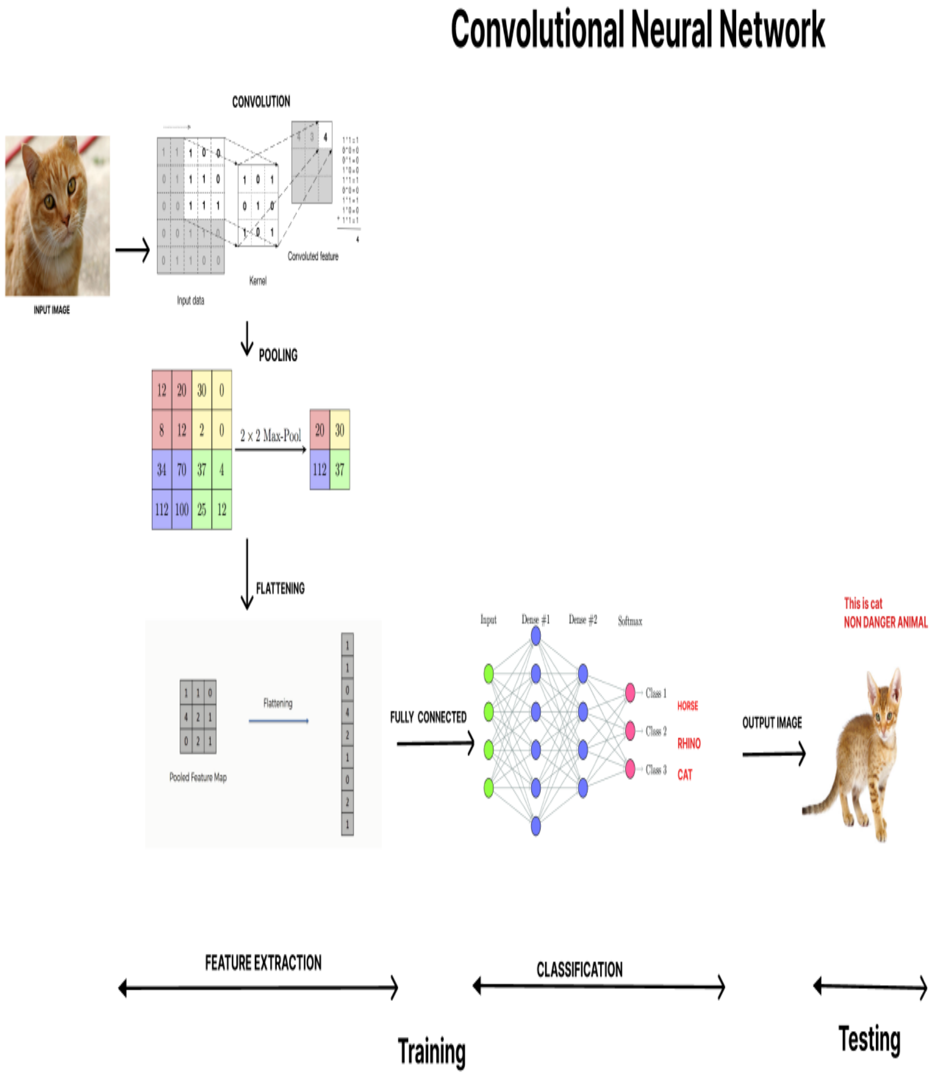

Figure:1: Proposed Methodology

Training and Validation

To train the deep learning algorithm, the dataset must be divided into two parts: the training set and the validation set. The training set is utilized to teach the algorithm to recognize patterns within the images, while the validation set is used to assess the algorithm's performance during the training process. The training dataset is utilized to train the model with the Adam optimizer and categorical cross-entropy loss function, with a batch size of 412 and 10 epochs. The model's performance is evaluated after each epoch utilizing the validation dataset. The best model is determined based on the highest validation accuracy and is saved [15].

TRAIN DATASET

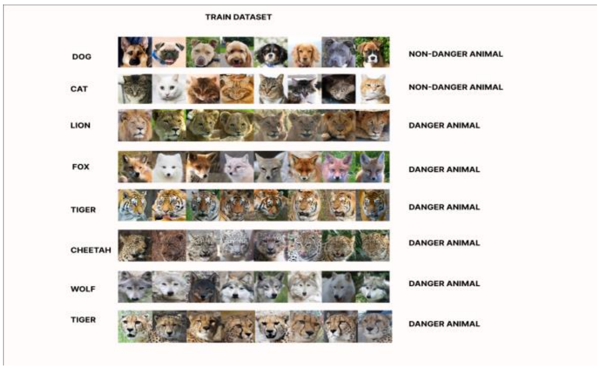

Figure:2 Animal Dataset

TEST DATASET

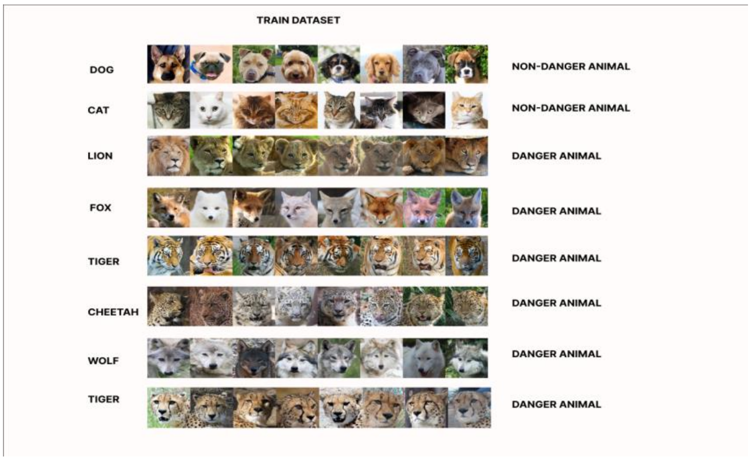

Figure:3 Animal Dataset

5. **Evaluation Metrics:** For the performance of our algorithm, we use evaluation metrics such as precision, recall, F1 score, and Confusion matrix.

A. **Accuracy**: The proportion of correctly classified images in the test dataset.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \quad Eq\ 1$$

B. **Precision**: The proportion of true positives (correctly classified dangerous animals) out of all the animals classified as dangerous by the model.

$$Precision = \frac{True\ Positive}{True\ Positive + Fasle\ Positive} \quad Eq\ 2$$

C. **Recal**l: The proportion of true positives out of all the actual dangerous animals in the dataset.

Vol 12 Issue 03 2023

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$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}\ Eq\ 3$$

D. F1-score: It is a measure of a binary classification model's accuracy, calculated based on precision and recall, with values ranging from 0 to 1.

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}\ Eq\ 4$$

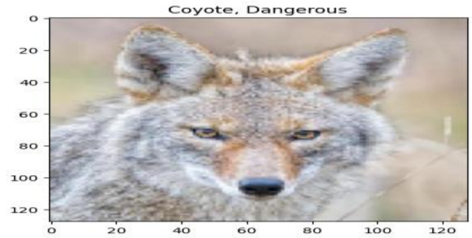
.

E. Confusion matrix: A confusion matrix is a 2x2 table used in binary classification that shows the number of true positives, false positives, true negatives, and false negatives, which are used to calculate precision, recall, and F1-score.

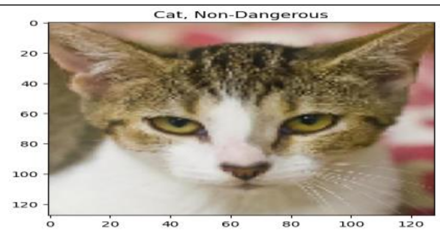
3. RESULTS AND DISCUSSION

This research is to promote responsible behavior around animals during wildlife tourism by providing accurate and reliable information on detecting dangerous and non-danger animals and safe distance guidelines. The successful implementation of a convolutional neural network (CNN) model to classify images of dangerous and non-dangerous animals.

WILD AND DANGEROUS



NON-DANGEROUS

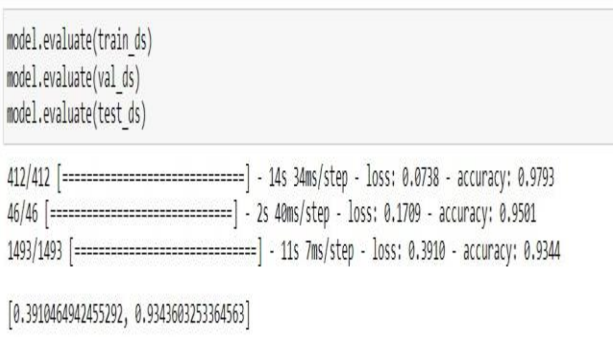


WILD-DANGEROUS

NON-DANGEROUS

Figure: 4 Classified Animal Category

The model achieved an accuracy of 98.26% on the training set, with a corresponding loss of 0.0592. On the validation set, the model achieved an accuracy of 95.63% with a loss of 0.1471. Finally, on the test set, the model achieved an accuracy of 93.28% with a loss of 0.4445. These results demonstrate the effectiveness of the model in accurately predicting the target variable.



```
model.evaluate(train_ds)
model.evaluate(val_ds)
model.evaluate(test_ds)
```

```
412/412 [==============================] - 14s 34ms/step - loss: 0.0738 - accuracy: 0.9793
46/46 [==============================] - 2s 40ms/step - loss: 0.1709 - accuracy: 0.9501
1493/1493 [==============================] - 11s 7ms/step - loss: 0.3910 - accuracy: 0.9344

[0.3910464942455292, 0.9343603253364563]
```

Based on the confusion matrix provided, the model achieved an accuracy of 93.28% on the test dataset, indicating that it can effectively distinguish between the two categories.When the scores for each category are examined, it can be observed that most categories were performed very well by the model, with high precision, recall, and F1 scores.

precision	**recall**	**f1-score**	**Support**
0.97	0.97	0.97	500
0.98	0.98	0.98	65
0.95	0.97	0.96	500
0.95	0.80	0.87	49
0.75	0.97	0.85	49
0.75	0.97	0.85	78
0.90	0.91	0.91	126
0.97	0.95	0.96	103

Table:1 Classification Results

The classification results showed that the model was effective in distinguishing between dangerous and non-dangerous animals. The implications of this research suggest that this type of model can be used for wildlife conservation efforts by helping to identify and track endangered species, as well as identifying potential threats to human safety in areas where dangerous animals are present.

4. CONCLUSION

In this research, the effectiveness of using a convolutional neural network (CNN) for animal classification in the context of wildlife conservation and management was successfully demonstrated.

An accuracy of around 93% on the test set was achieved by the model, indicating potential application in real-world scenarios, such as the identification and tracking of dangerous animals in the wild and the reduction of human-wildlife conflicts. The robustness of the model was ensured through the pre-processing of data and split into training, validation, and test sets. Additionally, a sequential neural network with multiple convolutional layers, pooling layers, and dropout layers was utilized to prevent over fitting, further enhancing the accuracy of the model. The results of this study also highlight the power of deep learning algorithms in image recognition tasks and their potential for application in various fields beyond wildlife conservation. Overall, this research provides valuable insights into the potential of CNNs for image classification and their applications in real-world scenarios.

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