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IMAGE RECOGNITION USING A NEURAL NETWORK (USING CONVOLUTIONAL NEURAL NETWORKS)

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ABSTRACT
An essential decision in constructing a neural network for any application is determining the appropriate representation of the data for presentation. Advancements in training techniques, such as changes to data augmentations and optimization methods, have greatly contributed to the notable progress made in the field of image classification research. Identifying and categorizing animals presents a substantial obstacle for researchers. The classification of animals consists of five main categories: mammals, amphibians, reptiles, fowls, and fish, each including a wide range of species. Therefore, we present an innovative method for recognizing and assessing classifications of vertebrate organisms by the use of deep Convolutional Neural Networks (CNN). The main objective of this article is to improve an intelligent model based on CNNs for the precise classification of vertebrate animals using image data. Basically, the goal is to create an efficient system that can be applied in real-world scenarios, including environmental monitoring, automated biological research, and educational applications. This research focuses on developing an efficient approach for classifying vertebrate animals using a deep CNN. CNNs, inspired by the human brain's structure, are powerful deep learning models eligible of processing large image datasets to achieve high precision in recognition tasks. The study utilizes CNN architectures trained on the Kaggle dataset to evaluate their performance in animal image classification. Through the application of real-time data augmentation and dropout techniques, the proposed models demonstrated exceptional precision, achieving an accuracy rate of 99.6%.
Keywords: *Image Recognition, Machine Learning, Convolutional Neural Networks, Animals' detection, Classifications of animals, Neural Network.*

1. Introduction

Identifying and classifying animals is crucial for understanding biodiversity and protecting endangered species. Classifying animals using various methods, including convolutional neural networks (CNNs), helps reduce wildlife incidents that often result in death or injury. While computer-aided animal classification saves considerable time and effort, it faces challenges such as variations in light intensity, weather conditions, and the different positions of animals.

CNNs utilize the convolution operation to capture essential features by combining spatial and channel-wise information within localized receptive fields. Several recent approaches have shown that improving spatial encoding can boost a network's representational power(Hu et al., 2020) . For the last two decades, ConvNets with a few hidden layers have been utilized for object detection. They were previously successful in limited domains like face detection. Deeper ConvNets have recently resulted in dramatic improvements in detecting more general classifiers. this shift occurred, when the successful application of deep ConvNets to classification techniques was transferred to object detection in the ("region-based CNN") line of work (Bell et al., 2016) . A neuronal network consists of artificial 'neurons' that establish communication among themselves. Neuronal connections are assigned numerical weight values that are modified during training, allowing the network to accurately recognize images or patterns. The network is comprised of multiple layers of 'neurons' that perceive unique information. Each layer comprises numerous neurons that react to various combinations of inputs from the previous layers, as shown in Figure 1. The layers are structured such that the first layer recognizes basic patterns in the input, the following layers detect patterns within these patterns, and so on. Deep neural networks (CNNs) often employ 5 to 25 distinct layers to detect patterns(Pigou et al., 2015).

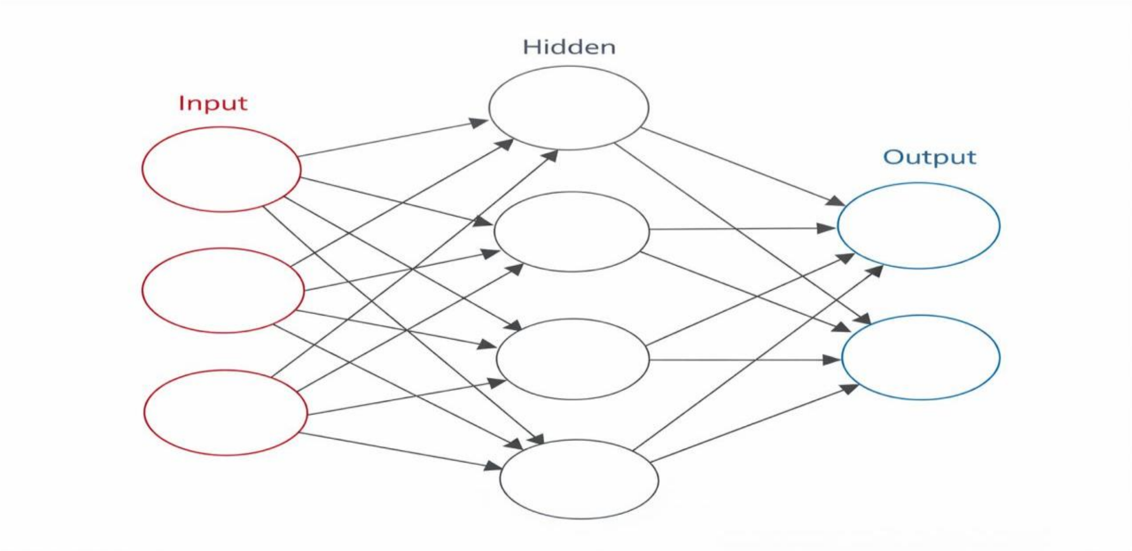


Fig. 1. An artificial neural networks(Pigou et al., 2015).

Biological neural systems inspire neural networks. A neuron is the fundamental computational unit of the brain, connected by synapses. Figure 2 illustrates a comparison between a biological neuron and a basic mathematical model. The training process is conducted using a "labeled" dataset that includes a wide range of representative input types, each linked to its designated intended output(Khan et al., 2018) .

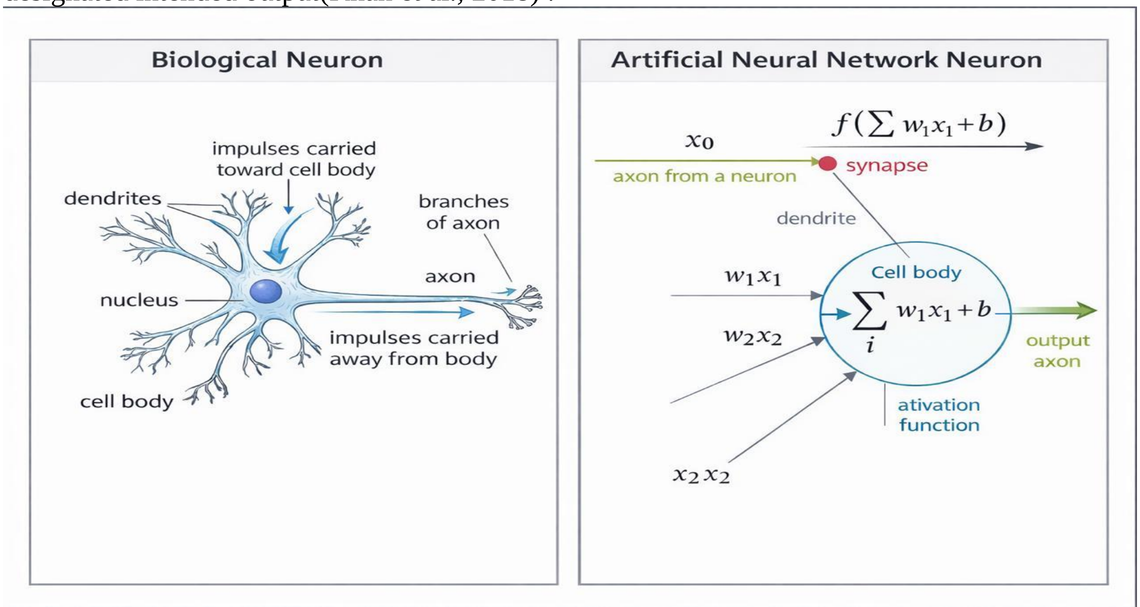


Fig. 2. Depiction of a biological neuron on the left and its mathematical representation on the right (Khan et al., 2018)

Higher levels of intricacy and detection layers do not always translate into higher accuracy. the more complexity, however, the slower the approach. While the two-stage Cascaded CNN technique produced a good outcome, it is more complex and slower. scheme pyramid networks for quick face detection using deep CNNs achieve extremely high precision and are a fast approach, that works preferably to other techniques in terms of accuracy and speed because the results are very reliable across different datasets. Proposal pyramid networks for fast face detection using deep CNNs are a preferable choice for the reasons stated above. Hierarchical

CNNs only performed well in one dataset and saw a decline in accuracy on other datasets (Dhahir & Salman, 2022). Using a vector as its input, the equation generates a one-dimensional array of values, where the greatest value matches the label with the greatest probability. The softmax function converts the observed output into probabilities, allocating the excessive probability of the output having the largest numerical value. The probabilities are added together to form one total probability. The user can determine which class label is predicted by converting the output of the softmax into one hot encoding vector. In conclusion, each neuron computes the bias, bias addition, and non-linearity as a trigger function (Shah & Kapdi, 2017).

CNNs are employed in various fields, such as speech recognition, natural language processing, image and pattern recognition, and video analysis. Several factors contribute to the popularity of CNNs. Unlike traditional pattern recognition models, which rely on handcrafted feature extractors, CNNs automatically learn features from data. In CNNs, the training process sets the weights for both the fully connected layer used for classification and the convolutional layer used for feature extraction. The enhanced network architectures of CNNs help lower memory and computational complexity, making them more efficient. This efficiency particularly benefits applications with local correlations, such as image and speech processing (Bell et al., 2016).CNNs can segment skin regions in images despite many skin detection challenges, such as skin tone, aging, race, gender, makeup, extensive tattoos, complex backgrounds, and more. This technique produced preferable results when compared to previous works. The previous networks focused on classifying images as skin or non-skin (Dhayea et al., 2024).A conventional vision algorithm pipeline, depicted in Figure 3 comprises four stages: image pre-processing, identification of zones of interest potentially containing objects, object recognition, and decision-making based on vision interpretation. The initial pre-processing phase is often influenced by the characteristics of the input data, while the final decision-making phase at the end of the pipeline usually focuses on the recognized objects. Although these decisions can be complex, they are based on much smaller amounts of data, making them less computationally demanding and memory-intensive. The primary challenge lies in the object detection and recognition phase, where CNNs are currently making a substantial impact (Russakovsky et al., 2015).A key factor in differentiating among poultry breeds is color of their feathers. However, because feather color composition is complex, the validity of traditional manual classification methods is questioned. Feathers from different body parts, or even within in the same feather, frequently exhibit non-uniform coloration. Establishing a universally applicable definition for the color classification of poultry feathers is severely hampered by this complexity (Niu et al., 2025).Agricultural administration, environmental monitoring, and wildlife conservation all rely on the exact classification of animal breeds and species. However, manual observation subjective, time – exhausted, and unreliable in complex environments remains a key component of traditional identification techniques. CNNs in particular, have improved visual recognition performance and enabled automated feature extraction. Nevertheless, current models still struggle with accurate classification tasks, especially in practical situation(Kamepalli et al., 2021).

Using CNN models, this article applies image recognition techniques to the Kaggle dataset. Model implementation is examined and performance is assessed in terms of accuracy. Further sections of the article are structured as follows: section 2 offers a concise summary of previous research, section 3 describes the system methodology and elaborates on the implemented mechanisms, section 4 presents the results and performance measurements, and Section 5 concludes the work by proposing areas for future study.

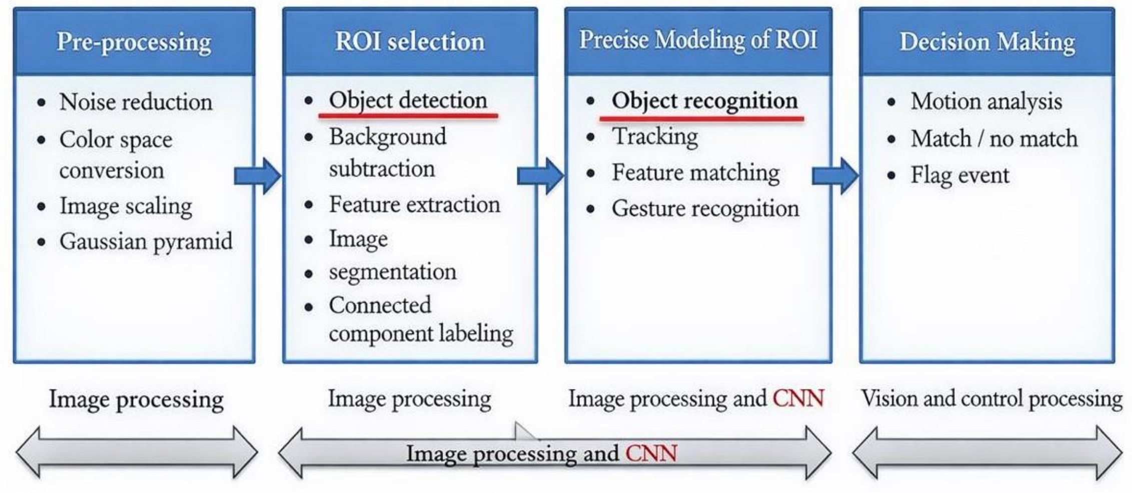


Fig. 3. Image processing algorithm pipeline.

2. Literature Review

An applied study was used to classify animals using CNNs model optimization strategies. Although accurate classification was achieved, the model faced several challenges, such as the small size of the data and the difficulty in exploring the link between diseases and animal behavior (Anuar et al., 2025).Furthermore, CNNs have been successfully applied in diverse fields beyond traditional image classification. For instance,(M. L. Shuwandy et al., 2025)proposed a multi-tiered CNN framework to enhance motor imagery analysis for UAV control within smart city environments. When compared to more conventional detectors like faster R-CNN(F-CNN), YOLO-FAC significantly enhances fine-grained wildlife species classification in complex environments'-CNN performs poorly in complex natural scenes with blur, occlusion, and visually similar species, despite its good localization capabilities. The improved model, on the other hand, gains from clustering-based feature analysis, which improves feature discrimination and lessens species confusion (Zhang et al., 2026). Similarly, in the domain of Arabic sign language recognition, deep learning models with attention mechanisms demonstrated significant accuracy gains(Abdul Ameer et al., 2024).Animal classification is essential. For biodiversity and the identification of endangered species, classifying animals by sight alone is laborious and costly. Over the past decade, deep learning networks have begun to classify and deliver sophisticated results. Convolutional neural networks (CNNs) require large amounts of data to achieve high-quality classification. A case study was conducted on a collection of images of wildlife, classifying them using CNNs under human supervision, especially for small-bodied species (Binta Islam et al., 2023). CNN-based feature extraction has also shown promise in biometric and smartphone authentication systems(M. Shuwandy et al., 2025), CNNs are highly efficient at classifying animals, and the models accuracy can be increased by adding several properly connected layers. As society has developed, people have become more familiar with dog, cats and rare wild animals; therefore, CNNs contribute to animal conservation (Yu, 2022). validating the robust capability of convolutional architectures in real-world applications. Furthermore, CNNs have been highly efficient in the automatic detection of pneumonia in X-ray images (Ahmed et al., 2021), further confirming their effectiveness in critical domains.

Presented here is a concise overview of previous research that has enhanced data to improve the performance of image classifiers. When a brain scan is performed using magnetic resonance imaging (MRI), which records the case of fonts with a fixed MRI width. curved baselines, which are common in brain scans, can be processed by (CNN) can process curves that frequently occur. The gaps are then split and analyzed. a constrained area above the baseline is examined, divided, and categorized. Contours are combined and reclassified to see if the recognition score has changed and if this does not improve the score. Small fixed-size patches over nearby contours are used to extract the features for classification, which are then compared to the deep learning representations that have been trained and can handle MRI sample results that are divided into multiple parts with ease thanks to this method (Shaker, 2021). Animal classification and ambulance recognition rely on CNN's ability to extract features from visual data, their goals, datasets, and performance criteria differ significantly (Darwassh Hanawy Hussein et al., 2022).

Several researchers have focused on improving fish species recognition by employing deep learning techniques. In order to overcome the drawbacks of manual identification, which is laborious and necessitates specialized ichthyology knowledge. In their study they applied the fusion visual attention graph convolutional networks FVAGCN approach to enhanced recognition performance under challenging underwater conditions. This approach aims to achieve more robust fish species recognition and higher classification accuracy than traditional CNN based method (Zhao & Dong, 2025). A CNN is a variation of a multi-layer perceptron (MLP) network and was utilized for the first time in 1980 (Fukushima, 1980). The human brain serves as an inspiration for CNN's computing. Humans use sight to recognize or recognize objects. Humans teach their kids to recognize objects by exposing them to hundreds of images of those objects. This helps a youngster recognize or predict objects that they have never seen before. Similar in operation, a CNN is widely used for visual imagery analysis. Among the popular CNN architectures are ResNet (152 layers), VGG (16–19 layers), AlexNet (8 layers), and GoogLeNet (22 layers). A CNN requires little pre-processing and feature extraction work and combines the feature extraction and classification processes. Rich and connected features can be automatically extracted from images by a CNN. Furthermore, even with minimal training, a CNN can offer a high degree of recognition accuracy (Jarrett et al., 2009).

A pre-trained CNN exhibits strong performance in detecting relevant patterns in biometric images, highlighting the benefits of CNNs and deep learning overall in the bio-crypto domain. Besides achieving good accuracy, using a pre-trained model offers the benefit of speeding up the matching process, as it eliminates the need for training from scratch. This approach could reduce the resource requirements of biometric systems. The success of CNNs in fingerprint matching has been established, underscoring the importance of Cosine similarity and Hamming Distance for precise matching. Furthermore, utilizing a Multi-task Cascaded Convolutional Neural Network (MTCNN) could improve matching outcomes even further (AL-Jumaili et al., 2023). Small datasets have the disadvantage of not generalizing well to data from the validation and test sets. As a result, these models suffer from overfitting. Various methods have been suggested to reduce overfitting (Wang & Klabjan, 2017). The simplest solution would be to include a regularization term based on the weight. A dropout is another common technique. During training, the leak may remove neurons from specific layers or break a specific connection (Russakovsky et al., 2015). Batch normalization is a widely used technique that normalizes layers and allows for the adjustment of normalization weights. It can be applied to any layer within a network, proving to be highly effective even in Generative Adversarial Networks (GANs) such as Cycle GAN. Transfer learning is the process of utilizing the pre-trained weights of a neural network, which has been trained on comparable or larger datasets, and subsequently adjusting particular parameters to optimize a more specialized problem (Xiang & Li, 2017).

used models include Long Short-Term Memory (LSTM), Gated recurrent units (GRU), and convolutional neural networks (CNN). The results showed that the GRU model performance yields more stable results than LSTM and CNN models concerning accuracy (Baker et al., 2023). Another method for reducing overfitting on models is data augmentation, which involves expanding the training data set by utilizing only the information from the existing training data. Data augmentation is not a new concept; numerous techniques have been employed to address particular issues. The primary technique is data warping, which involves directly modifying the model's input data in data space. This concept dates back to the augmentation of the Modified National Institute of Standards and Technology (MNIST) dataset (Bunke et al., 1994). Applying geometric and color augmentations, including reflecting, cropping, translating the image, and adjusting its color palette, is a widely accepted and common approach to enhancing image data. These transformations are all affine modifications of the original image. This method achieved a 0.34% error rate by creating new training samples through data augmentation techniques applied at each layer of a deep network. In particular, digit data were enhanced using elastic deformations alongside standard affine transformations. Furthermore, data augmentation has shown benefits beyond merely expanding the dataset size (Pashine et al., 2021). Red fox image classification uses information from a variety of sources, including game captured images, real photos, and content produced by AI. The effectiveness of deep learning models(inception V3,VGG-16, and VGG-19) for feature extraction and their combination with conventional classifiers support vector machines(SVM) and logistic regression in hybrid framework. Clustering quality and class separability were examined using t-SNE,MDS, and silhouette measures on dataset of 400 images in four categories. The findings show that robustness and accuracy in multi-source image classification are greatly increased when deep learning feature extractors are combined with traditional machine learning classifiers, supporting applications in synthetic media analysis and wildlife monitoring(Sabayu & Yuadi, 2025).

To increase accuracy, use a method that uses 1D CNN for feature extraction and machine learning (ML) algorithms like XGBoost, random forests (RF), decision trees (DT), support vector machines (SVM), and k-nearest neighbor (KNN) to classify samples as benign or malignant. show that the accuracy of the XGBoost algorithm with feature extraction (1D CNN) on the test set was 98.24%. employs a Wisconsin breast cancer (WBC) dataset to identify breast cancer (Nafea et al., 2024). Finally, we investigate methods for training the neural network to simultaneously augment and classify data. A similar approach was previously attempted, where different weights were learned to integrate existing techniques. In our work, we seek to create a style transfer network that can learn to generate data augmentations as efficiently as possible. The purpose of augmentation is not only to reduce overfitting but also to enhance the data in a manner that most effectively boosts the classifier's performance.

3. Research Methods

In this Section, the methodology of the proposed kind detection model will be presented and illustrated in details. In this study, the essential technique that has been suggested to implement the image detection model requirements is the convolutional neural network (CNN) algorithm.

Any classification system relies on its ability to identify the key attributes and features upon which classification is based to achieve the desired goal. Any model depends on raw data from the external world, which may not be ideal images for classification. Therefore, the application must process images before classification. Some challenges that affect the classifier's performance must be mitigated, such as light intensity, blurred backgrounds, or lighting issues, especially at night. Also, the CNN algorithm will contain an important function called the activation function, which will be necessary to generate the feature maps or the activation maps using the ReLU activation function. One more group of Artificial Intelligence (AI) models is the territorial-based Convolutional Brain Organizations Fast Regional Convolutional Neural Networks (FR-CNN) that are applied for PC vision and explicit object location. Thus, the main objective is to enable the classifier to extract features optimally from images in order to classify them with minimal loss and maximum accuracy.

Proposed system design: the system can be divided into four part (data collection, preprocessing, resampling and model building)

A. Data Collection: -
The input is based on a dataset from Kaggle, which comprises approximately 5,400 animal images taken in the wild.

B. Pre-processing:-
Images taken from the outside world contain a lot of distortion and noise, so at this stage, removing the distortion is essential to ensure the algorithm works efficiently. K-means is used for segmentation if you can remove the background image, leaving the animals in the image.

C. Re – sampling:-
At this stage, a significant imbalance between the categories was observed. To increase the sample size, some samples were collected from the original data using zoom, flip, and rotate techniques.

D. Model Building:-
When images were deemed suitable for training, various models, including VGG16, Inception V3, ReLU, DCNN and FR-CNN, were built to classify the images into multiple categories. FR-CNN was found to achieve the best classification results after training on 50 epochs, based on the Kaggle training set containing over 5,400 samples. Data augmentation

was used before feeding the model for training to achieve data diversity. This involved using the initial weights employed in the CNN layers as optimal weights for training FR-CNN. The entire model underwent weight changes through feedback during a phase of interconnected layer circulation. The first and second layers contain over 512,200 neurons, while the third layer contains 8 neurons with Softmax activation and cross-entropy loss for the category. When over-processing occurred, a drop layer was added between the first and second layers to cut 20% of the connections between them. Model performance was evaluated based on classification accuracy. The models demonstrate higher classification performance when a limited amount of data is available for training.

Also, the entered datasets have been introduced and explained in which they will be utilized to train the suggested model algorithm.

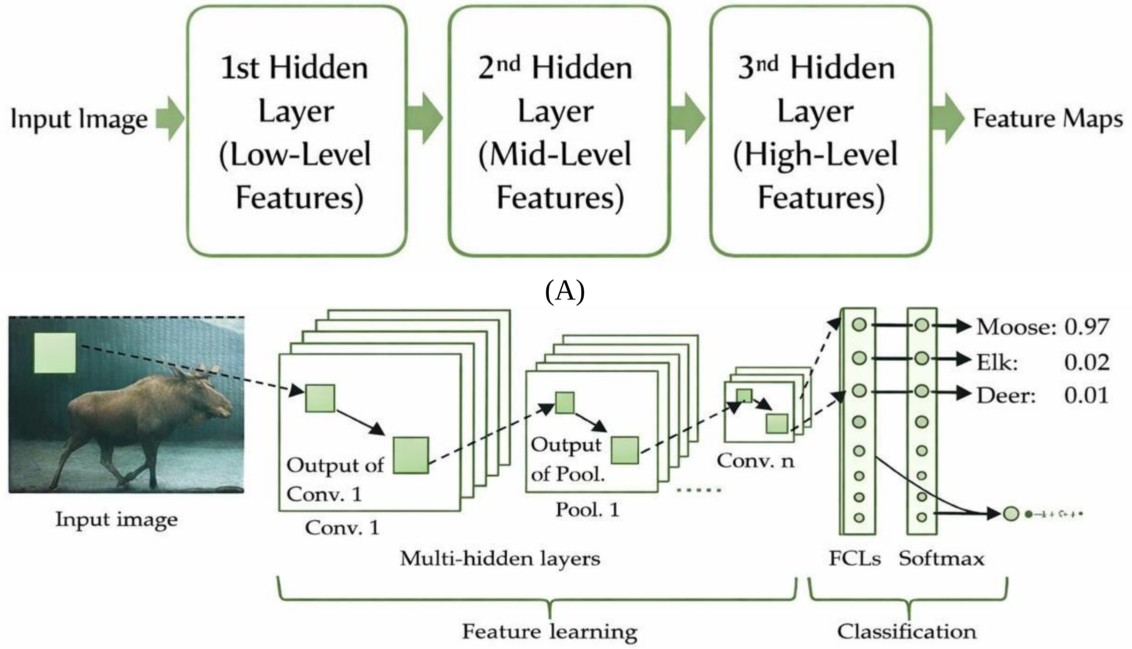
3.1 SoftMax

Softmax, often referred to as the normalized exponential functions used for multi-class classification tasks. It normalizes the input into a probability distribution that sums to 1. Both the Softmax and sigmoid functions take an input vector, represented as X, which consists of x elements from x classes, as calculated below:

$$\text{Soft Mask} = \frac{e^{x}}{\text{sum}(e^{x})} \qquad (2)$$

3.2The Proposed Model Description

In this section, the CNN algorithm model suggested for kind object recognition and detection will be described and comprehended with details. Figure 4 shows a block diagram of the FR-CNN algorithm utilized in the suggested kind object detection model. The main operation of the first stage of the FR-CNN algorithm will be the features extraction using the deep learning CNN layers technique. The second stage of the FR-CNN algorithm will be as classifier that will classify the results obtained from the CNN operation of the first stage. The above presented Region R-CNN algorithm diagram in Figure 4 will be implemented and simulated utilizing MatLab2020b Simulation program with m. files codes scripts. The flow chart of this simulated FR-CNN algorithm is introduced in Figure 5.



(A)

(B)

Fig.4. The suggested FR-CNN algorithm for kind object detection model, (A) Demonstration of the structure of DNNs consisting of several hidden training layers of extracted features, (B) Internal layers structure.

By observing Figure 5, the flow chart of the suggested FR-CNN algorithm, it is obvious that the flow chart of the FR-CNN algorithm will compose from several succeeded layers. The entered image will be first pass through the convolutional layer1 that will apply the features filtering and mapping operations. Next, the Relu function1 will reduce the weights of the data extracted from the convolutional layer1 for the purpose of enhancing the feature filtered and mapped data. Then, the resulted data will be passed through the convolutional layer2 for further features filtering and mapping. After that, applying the Relu function2 to increase the data precision. The next layers in our proposed R-CNN algorithm are the features classification1 and features classification2 those will represent the regional classification of the CNN-analyzed data. The final stage in this suggested (R-CNN) algorithm is the SoftMax function that will apply the final softening to the resulting data. In this study, the suggested model for kind objects detection and recognition will be implemented utilizing MatLab2020b m. files script codes. We will implement FR-CNN algorithm technique by assisting with the built-in functions supported by MatLab2020b software. The utilized built in function was the "train FRCNN Object Detector" deep learning object detector that will require the Statistics and Machine Learning Toolbox (TM) and the Deep Learning Toolbox (TM) to apply such function. Next, the FR-CNN algorithm simulated model from entering data to the output results have shown in Figure 6 below.

In Figure 6, the presented detailed structure of the FR-CNN algorithm simulated model will have constructed from powerful built in functions operating to perform the deep learning procedure to the entered datasets. All the necessary blocks such as; featuring filters, convolutional layers, pooling functions, Relu functions, and classification utilities are available in this project, the proposed model of the FR-CNN algorithm model to perform the necessary animal kind detection and recognition missions.

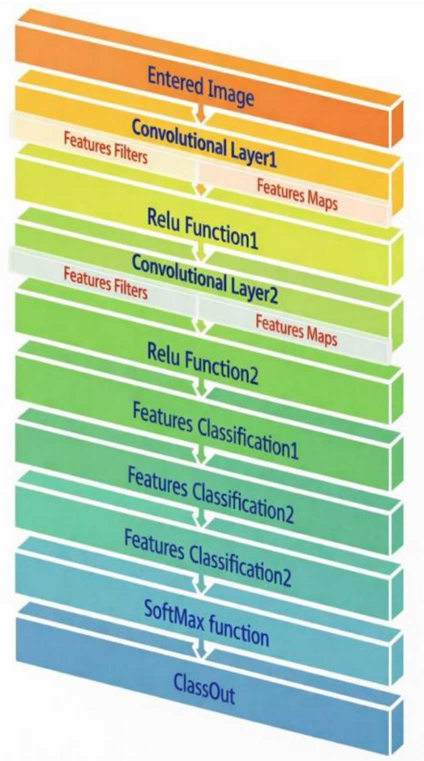


Fig. 5. The flow chart of the simulated FR-CNN algorithm utilized for kind object model

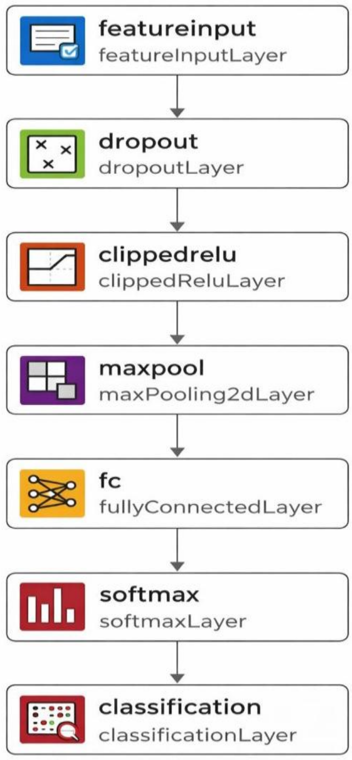


Fig. 6. Structure of simulated FR-CNN algorithm

The previous discussed FR-CNN suggested algorithm will be trained in our simulated program using various training images data set containing all the emotions of the animal kinds. The data set used is from Kaggle, which contains a training set and a test set. The animal kind data sets have been classified according to the typical kind objects, as below:(American Bull, Cheetah, Delphinapterus, Dogs, Ducks, Frogs, Kangaroo, Lions, Mammuthus -primigeniu, and Octopus). These categories will represent the most known objects available in the animal kinds. In fact, the entered datasets to the deep learning FR-CNN algorithm have been divided into two types, the validation set and the training set. Each picture from the validation set will be utilized to test the FR-CNN algorithm individually, while the training set will be all utilized to train the FR-CNN algorithm. Samples of the validation dataset are presented as shown in Figure 7.

Fig. 7. Samples of the tested validation datasets using deep learning FR-CNN algorithm.

In kind detection issue, and as previously mentioned that each set of the entered dataset of the validation and the training consists of 10 categories representing the most realizable kinds of the animal objects. Figure 7 illustrates the validation dataset samples of the Lions objects which have more than 100 picture for different situations in size and motion. Also, several samples of the training dataset are introduced as shown in Figure 8.

Fig. 8. Samples of the training datasets applied to train the deep learning FR-CNN algorithm

Figure 8 demonstrates the training dataset samples of the American bull kind which have more than 50 picture for different shapes in size and angle. Actually, these animal pictures dataset will be utilized to train and test the suggested FR-CNN algorithm to detect the exact kind in the entered tested picture sample. The implementation of this suggested model will be illustrated and explained in the next Section, and the achieved results will be well demonstrated with sufficient discussion.

4. Results and Discussion

The findings of this study align well with previous research that emphasizes the versatility of CNNs in various application domains. Notably, (M. Shuwandy et al., 2025) integrated CNNs with decision-making techniques to enhance the robustness of smartphone biometric authentication, demonstrating significant improvements. Similarly, the successful application of CNNs for the automatic diagnosis of pneumonia from X-ray images, as detailed by (Ahmed et al., 2021), underlines the high accuracy potential of convolutional models in sensitive healthcare domains.

The following section provides and analyzes the findings of the experiment. The proposed feature selection strategy was applied to the datasets, and the classifiers were trained using the animal detection model with the CNN algorithm, a specially configured graphics card: NVIDIA GeForce GTX 960M, 16 GB memory (RAM), and 512 GB storage had to be shifted down to a normal grid for running more than an estimated 30 minutes (training). For the processing and inference part of the allocated VM(Virtual Machine), there was an Intel (R) Core (TM) i7 2.3GHz processor used before the training. All images were resized to 299 x 299 pixels, which was implemented in MATLAB 2020b using .m file codes. The simulation structure of the proposed scheme has been designed and prepared to satisfy the dataset requirements discussed and presented previously. The final model is multi-class classifier that can categorize wildlife into 5 categories. Butter results were obtained by training the model for 50 epochs. The Adam optimizer with initial learn rate of 0.000001. The figure 10 display accuracy versus epochs and loss versus epochs, respectively. The accuracy of the model when tested with a standardized image set randomly selected portion of the original dataset is shown in Table 1.

Table 1-The design parameters utilized to set the implement the simulation model

Design Components	Learn Rate Schedule	Mini Batch Size	Max Epochs	Initial Learn Rate	Plots
Value	'piecewise'	20	50	1e-6	Training-progress

4.1 The Achieved Results

The simulated model has been implemented using the suggested FR-CNN algorithm with the imported dataset of the animal kind classifications. The results of this simulation have been obtained and illustrated as below: Figure 9 is reading data image”lions” ,Figure 10 illustrate the training progress of the suggested FR-CNN algorithm for “Lion” category, Figure 11 detected animal kind data image for “Lion” category, Figure 12 The training process details of the suggested FR-CNN algorithm for “Lion” category.

Fig. 9. Test image for “Lion” category.

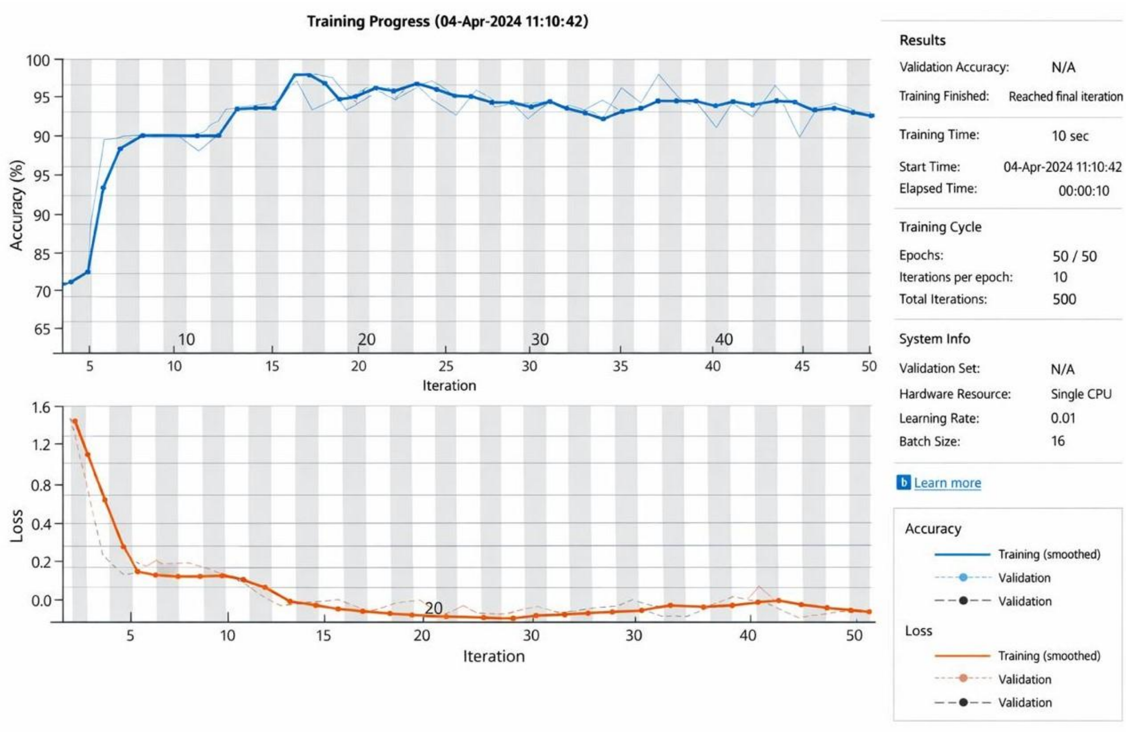


Fig. 10. The training progress of the suggested FR-CNN algorithm for “Lion” category

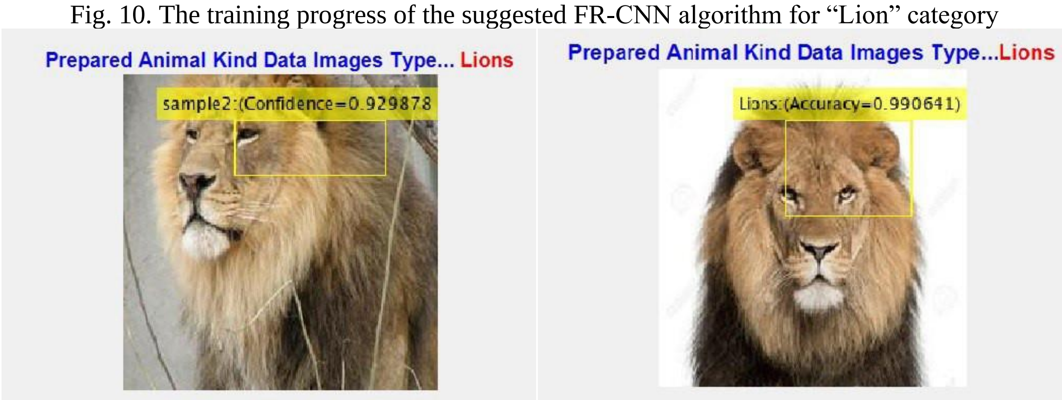


Fig. 11. The detected animal kind data image for “Lion” category

--> **Training** a neural network to classify objects in training data…

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:07	25.00%	1.9317	1.0000e−06
17	50	00:00:19	90.00%	0.2922	1.0000e−07
34	100	00:00:29	80.00%	0.2959	1.0000e−09
50	150	00:00:40	80.00%	0.4544	1.0000e−10

Network training complete.

--> Training bounding box regression models for each object class…100.00%… done.

Fig. 12. The training process details of the suggested FR-CNN algorithm for “Lion” category

Figure 13 detected animal kind data image for “Mammuthus” category, Figure 14-15 The training process details of the suggested FR-CNN algorithm for “Mammuthus” category.

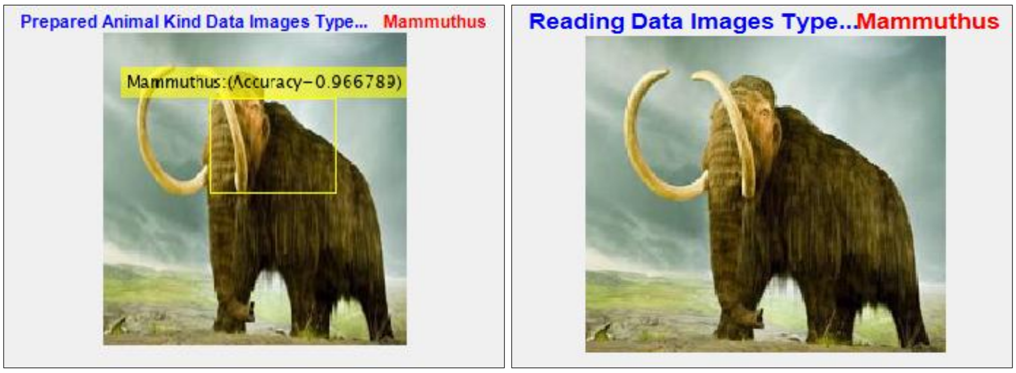


Fig. 13. Test and detected image for “Mammuthus” category

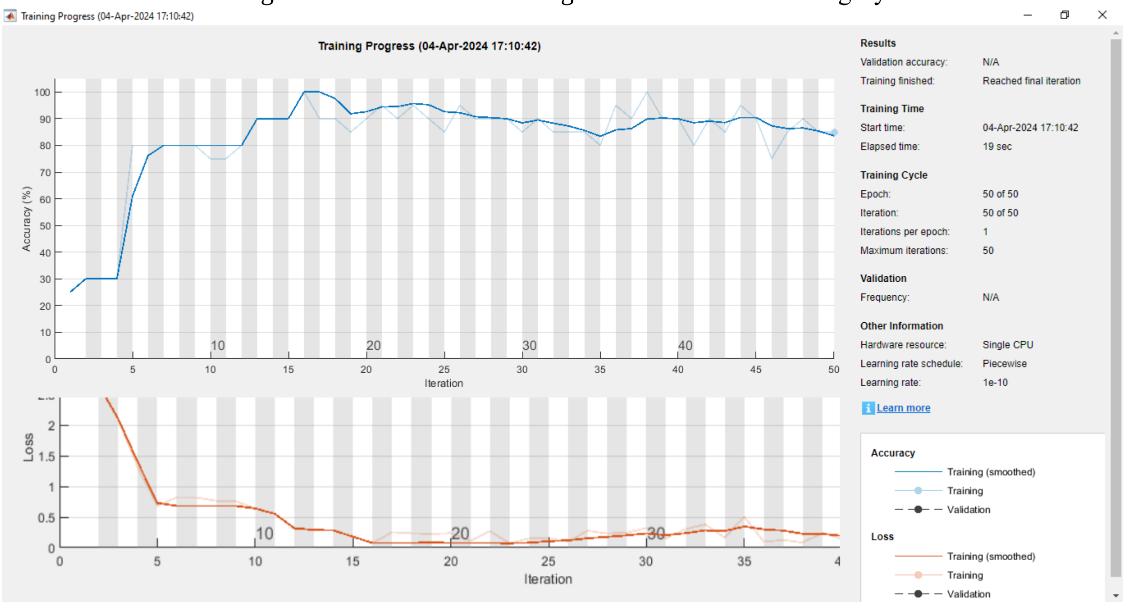


Fig. 14. The training progress of the suggested FR-CNN algorithm for “Mammuthus” category

```
--> Training a neural network to classify objects in training data...

Training on single CPU.
Initializing input data normalization.
|======================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Mini-batch  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |     Loss     |      Rate       |
|======================================================================================|
|       1 |           1 |       00:00:06 |       25.00% |       3.1141 |      1.0000e-06 |
|      50 |          50 |       00:00:19 |       85.00% |       0.1940 |      1.0000e-10 |
|======================================================================================|

Network training complete.

--> Training bounding box regression models for each object class...100.00%...done.
```

Fig.15. The training progress details of the suggested FR-CNN algorithm for “Mammuthus” category

The accuracy and efficiency of the proposed method, as shown in Table 2, is higher compared with many other similar works.

Table 2 - Comparative analysis of the proposed approach with other approaches

No.	Research Goal	Method	Test Accuracy %
1	The animal image classifier is implemented using a CNN. This classifier can efficiently distinguish between three categories: cats, dogs, and wildlife, based on the trained models (Yu, 2022)	The researchers employed a CNN and evaluated the neural network using accuracy and loss as metrics. Optimization was performed using the Cross-Entropy loss function.	Above 90%
2	Utilizing a camera-trap database with potential animal sightings identified through a multilevel graph cut in the spatiotemporal domain, developed an algorithm for wildlife monitoring and analysis through animal detection (Verma & Gupta, 2018)	Application of a Deep Convolutional Neural Network (DCNN) features in an animal detection model, resulting in a high level of accuracy on a standard camera-trap dataset.	91.4%
3	Using (DCNN) to detect and classify the animals (vertebrate classes) in digital images (El Abbadi & Alsaadi, 2020).	Involved using a Deep (CNN) for animal detection and classification in digital images, utilizing a dataset of 12,000 images with specific training and evaluation splits, determining the optimal image size and number of epochs	97.5%
4	The CNN model utlilzes demonstrative estimation and way of acting classification of boroiler chickens (Fang et al., 2021)	Was utilized the Naive Bayesian Model (NBM) to classification chickens poses and recognizing	93.71%
5	Deep learning technology has been employed to identify images for addressing sentencing issues in forest resource enforcement cases(Yin & You, 2020).	Apply data enhancement mechanism to rotate the original image, use major component analysis to minimize dimensionality and eliminate redundant features, and achieve small sample classification through transfer learning.	88%
6	Develop an accurate and efficient animal recognition model and strike a balance between recognition accuracy and model size to improve its feasibility on mobile devices(Jiang et al., 2019).	The Bilateral Convolutional Network (BCNet) aims to balance recognition accuracy and model size, making it more suitable for implementation on mobile devices.	85.6%
7	developing an animal face classification system using a dual DCNN, enhancing feature extraction capabilities, building a dataset with ten animal classes, mitigating overfitting, and improving learning through image augmentation (Khan et al., 2018).	Application of a fully connected dual Deep Convolutional Neural Network (DCNN) with a small batch size and a high number of iterations to avoid overfitting, together with the use of image augmentation to enhance learning.	%92.0
8	Using (CNN) to detect and classify animal meat (G C et al., 2021).	The classification of beef cut images was tested, validated, and trained using two pretrained (CNN) models: Visual Geometry Group (VGG16) and Inception ResNet V2	(VGG16) 98.6% ResNet V2(95.7%)
9	Constructing the Stanford Dog Dataset to categorize dog breeds by integrating image features from four CNN models, applying PCA and GWO to filter features, classifying features with SVM, and attaining superior classification accuracy rates compared	they utilized transfer learning, Stochastic Gradient Descent (SGD), principal component analysis (PCA), gray wolf optimization algorithm (GWO), and support vector machine (SVM).	95.24%

	to alternative approaches(Cui et al., 2024).		
10	Can successfully protect rare animals by using the CNN model to identify them early. CNN will therefore be useful in the field of animal conservation, particularly with regard to rare species (Zeng, 2021).	used CNN to separate images and worked on classifying similar animal images using a basic 2D CNN in Python.	96.67%
11	(CNN) were used to design an Internet of Things (IoT) based acoustic classification system, which is useful for environmentalists, zoologists, and animal scientists who are interested in monitoring ecosystems (Vithakshana & Samankula, 2020).	collect information from its location. The audio clips were preprocessed using the Mel-frequency Cepstral Coefficient (MFCC). A CNN architecture based on TensorFlow was used for training. The network was trained and tested using 400 two-second sound clips. The network was trained using different gradient descent optimizers, and the confusion matrices for each were ultimately determined. The optimal results were obtained using the AdaDelta, Gradient Descent, and RMSProp optimizers.	91.3%
12	Using (CNN) to detect and classify image.	Involved using a DCNN for animal detection and classification in digital images, AI models are the territorial-based Convolutional Brain Organizations' Fast Regional Convolutional Neural Networks (FR-CNN) that are applied for PC vision and explicitly object location.	99.6 %

5. Conclusion

The results clearly indicate that the pre-trained CNN exhibited tremendous efficacy in detecting patterns within biometric images. This stresses the capacity of CNN and deep learning in bio-crypto. Although CNN may not supplant conventional methods, it can serve as a supplementary technique due to its exceptional image feature analysis capabilities. The model was applied to a dataset from Kaggle, and the model was trained using the backpropagation algorithm and performance optimization techniques such as pooling and normalization that have undergone training on a large dataset of images, improving the precision of image feature articulation. Employing a pre-trained model not only attains satisfactory accuracy but also accelerates the matching process by eliminating the necessity for initial training, so minimizing the resources needed by biometric systems. The large size of the pre-trained model enables it to process a wide range of datasets efficiently. One major limitation of this work is its narrow focus on a single dataset. However, the adaptability of Kaggle models allows them to be used with different datasets. Although the accuracy achieved is satisfactory for real-world use, accurately detecting wildlife at night, only in the absence of natural light, represents the most challenging and impactful expansion

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