

Animal Footprint Classification using Machine Learning and Advance Deep Learning Methods

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Abstract: Categorization of animal footprints is a significant aspect of ecological research, conservation, and wildlife monitoring. Here in our research, we introduce a novel method to identify and classify animal footprints through the application of state-of-the-art deep learning and machine learning methods. An ensemble model combining "Xception and NasNetMobile" is primarily discussed, but "ResNet50, InceptionResNetV2, DenseNet, MobileNet, Xception, and NasNetMobile" are also used in the classification task. Contemporary algorithms like "YOLOV5x6, YOLOV5s6, YOLOV8n, and YOLOV9n" are utilized for footprint identification. The proposed ensemble model performs the highest classification accuracy by combining Xception and NasNetMobile. In the case of footprint identification, YOLOV5x6 was the superior method since it resulted in astounding outcomes with excellent precision. The efficacy of the models could be measured through calculating measures such as "recall, precision, and F1 score" evaluations. Results reveal that such cutting-edge deep machine learning algorithms find application in environment and wildlife research by simplifying and enhancing identification and categorization of animal footprints.

“Index Terms – Footprint Classification, Machine Learning, Deep Learning, YOLO, Ensemble Model, MobileNet, Xception, DenseNet, InceptionResNetV2, ResNet50, NasNetMobile”.

1. INTRODUCTION

The ability to identify and classify animal footprints has become an important component of wildlife surveillance systems, ecological studies and conservation efforts. The health and dynamics

of the ecosystem can be postponed through the analysis of animal tracks, which indirectly acts as a powerful marker yet of the species' presence, behaviour and migration pattern. Time, scalability and coverage areas were traditionally prevented when it came to identifying and analysing the

animal footprints, which required skilled experts to conduct labour-intensive manual inspection [1]. Deep learning techniques are implemented for observation of wildlife in response to the increasing demand for scalable and more efficient surveillance systems. Improving the accuracy and speed of data collection, these refined algorithms can automate the process of detecting and classifying animal footprints [2].

Systems that can identify animal tracks in different environments have recently become possible due to growth in data vision and artificial intelligence. Deep learning techniques are capable of solving the differences between complex areas, partly prints, overlapping tracks and small species, which separate the footprints by training models on a mass dataset of annotated footprint [3]. The ability of a convolutional neural network (CNN) to learn the spatial hierarchy of data has promoted their widespread use in recognition work and their unique performance in image classification tests [4]. Another advantage is that these systems can be installed using mobile devices, video or drones in real time, providing the possibility of continuous monitoring with any human participation.

Using automated footprint classification will have far-reaching consequences. Their detection and movement monitoring of endangered species is just one way they help with biodiversity conservation; they also lend a hand with anti-poaching efforts and habitat protection programs [5]. Particularly in conventional feature-based methods, combining Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Local Binary Pattern Histograms (LBPH) increases recognition accuracy in some systems even further [5]. In addition, Amur tigers and other individual species have been successfully tracked in icy conditions using non-invasive footprint identification

techniques, demonstrating their usefulness in delicate conservation areas [7].

Due to their shared environment and strikingly identical printing companies, it may be difficult to distinguish the footprints of the species related to carefully; However, new research hybrid machines are investigated by learning methods that merge the morphological analysis with deep learning to solve this problem [8]. A revolutionary change in the collection and interpretation of organic data for animal protection is on the horizon, which increases the availability of label footprints data sets and thanks to the rapid development of stronger and general models [6].

2. RELATED WORK

Animal recognition, behavioral analysis and environmental monitoring have all seen a dramatic use of ML and DL methods in recent years. Identification of species and automation of pre-manual processes such as classification of animal footprints is becoming more common with the use of these technologies. For conservation efforts, a game-skinned, artificial intelligence (AI) has been widely used to create powerful algorithms under the supervision of wildlife that can identify species, analyze habits and spot hazards in real time [9].

Researchers in the region have investigated several different identity methods, including image-based recognition and sensor-based activity monitoring. Non-infectious and compatibility with the current video Trap system has contributed to the increase in the popularity of the recognition of image-based species among these. From simple manual classification to complex data view models that use CNN and other deep learning architecture, the methods of recognition of animals and individuals have evolved [10]. Thanks to these techniques, we

can now classify animals exactly into different types of houses, from water to country and even sky. Training and verification procedures for these models have also increased sharply by the increasing availability of the dataset on a large scale.

For example, research on marine biodiversity has utilized deep learning techniques, although taxonomic identity always needs a lot of human efforts. Researchers have greatly improved the accuracy and speed of the classification of species using convolutional neural networks (CNN) and transmitted learning methods, especially in the underwater settings [10]. This development provides an example of how different ecological learning methods can be used at the bottom. Similarly, AI has shown a promise in monitoring farm animals to see behavior, health and abnormalities in dangers; This data is important to reduce livestock loss and improve animal welfare [11].

Complex animal activities have modelled using deep learning in behavioural analysis. To detect and understand the pattern of behaviour, these models often use a mixture of images and data collected from motion sensors. Nerve networks, recurrent architecture and multimodal data transaction have been postponed in recent studies, which have investigated the approaches used to predict behaviour [12]. Researchers have improved the ability to classify the behaviour of wild animals by combining ocular inputs with data from accelerometer and GPS sensors. The use of deep temporary models is to improve the reliability of activity recognition in the sensors such as animals are carried. These models are able to identify both common and unusual features [13].

Prophets of animal extermination and decline in the population have also used deep learning forces. These models use data on environment, biology and behavior, which are intended to detect trends that may indicate adjacent dangers of the existence of species [14]. To compete with creeping, preserve migration paths and rescue houses, turn protectionist future analysis to analysis. In addition, autonomous monitoring platforms are developed as a result of progress in intelligent surveillance systems. Often operated by the underlying AI pieces, these systems can provide, classified and give real -time notification without continuous human inspection [15].

When it comes to classifying animals, many different deep learning architectures have been tested. These include transformer -based models, CNN and resnets. Data set quality, car dividend and species variability all play a role how well these designs have performed well. By integrating the results of several algorithms, some examples have used the clothing model to increase the strength of the classification [16]. A large number of species try to identify specific persons when they work with or within a species, these methods actually shine.

Scalability of AI and related technologies is displayed by their integration into poultry and agricultural environments. Research on poultry has used condition - -Art deep learning systems to track the activity level of chickens kept in packaging without bars and identify unusual behavior. Not only can these devices make animals happy, but they also collect data that can help with things like preventing and increasing production [17]. Similarly, the monitoring system operated by AI has been installed near railway tracks to identify the animal movement and immediately informed the authorities, so prevent confrontation with

wildlife. For effectively covering locations with high risks, these solutions integrate object detection algorithms with remote monitoring frameworks [18].

Recent developments in machine learning have also been useful for classifying marine species, especially with sonar imaging and arrival of underwater cameras. Recent research examined many deep learning models for classification of underwater species, such as mass imbalances, light ups and downs in the form of major obstacles. In many cases, improved solutions, including domain adaptation, attention mechanisms and computer text, powerful performance of the model [19]. In addition, AI tools, breed classification and movement driving for the prediction of the disease have been introduced as part of the digital change of livestock management, especially in sheep cultivation. In addition to adapting resources and human treatment of animals, these applications increase agricultural efficiency [20].

All of these new progress sheds light on how AI and DL bring revolution in animal tracking and classification. The intelligent system has revolutionized research, protection and policy design automatically by automatically and enables large and more accurate data analysis by automatically and enabling large and more accurate data analysis. With the use of these technologies, ecological studies can quickly collect data and determine in real time, which helps preserve biodiversity and lasting practice.

3. MATERIALS AND METHODS

The proposed approach applies deep learning models to classify and detect animal footprints automatically, thereby enhancing ecological surveillance and conservation efforts. Classification

is performed using architectures like "ResNet50, InceptionResNetV2, DenseNet, MobileNet, Xception, and NasNetMobile", and an ensemble of "Xception and NasNetMobile" is used to increase accuracy by learning diverse feature representations [9], [10], [16]. YOLO-formulated models, i.e., "YOLOV5x6, YOLOV5s6, YOLOV8n, and YOLOV9n", are used for real-time footprint localization and generate fast and accurate detection suitable for dynamic environments [11], [18]. The system is trained on a carefully curated dataset of animal footprints and tested by using "precision, recall, and F1 score criteria [14], [17]". The method improves wildlife protection efforts through automation of identification and detection, circumventing limitations posed by human tracking, and drawing on prior successes in deep learning for monitoring animals and smart surveillance [12], [15], [20].

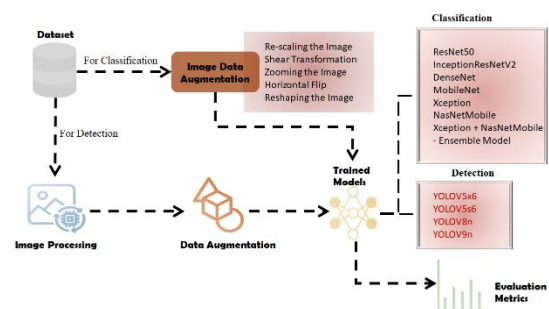


Fig.1 Proposed Architecture

This diagram illustrates a comprehensive image analysis process involving classification and detection tasks. Starting from a dataset, the process branches out: for classification, images are augmented by varied alterations like re-scaling, shearing, zooming, flipping, and reshaping, thus enhancing model resilience. At the same time, images are analyzed and augmented for training detection models. Used models like ResNet50, InceptionResNetV2, and variants of YOLO are used for specific applications. Ultimately,

evaluation metrics are used to measure the performance of the models, providing insights on their accuracy and effectiveness in both classifying and identifying objects in the images.

i) Dataset Collection:

The Animal Foot-Print Dataset is a carefully unified collection used for training and assesses deep learning models in the detection and classification of animal footprints. This includes high resolution of footprints taken under different environmental conditions representing several species. Each image is marked with the right species and in some examples of temporary data to facilitate the prediction of behaviour. This dataset is required to automate footprint identity tasks by offering separate and label examples, so the development of a strong classification and detection system supports. Use clearly reduces dependence on manual tracking techniques and expert rating.

ii) Pre-Processing:

To guarantee the best possible input for deep learning models, pre-processing paintings improve quality and uniformity. This package increases training efficiency, accuracy and model generalization in different environmental conditions and animal footprints. This includes image scaling, growth, format conversion and adjustment of annotation.

a) Classification: To make the classification model more reliable and efficient, image data is expanded using a wide range of enrichment methods. This process begins by shaping images to make pixel values uniform, and then move towards shrinking changes and zooming to mimic the distance and perspective. To be continuous entrance dimensions

in all photographs, size is used, and horizontal flip is used to promote variation. The model is able to avoid overfitting and learning from a broad dataset using these growth strategies. The classification algorithm is able to identify different species and environmental conditions correctly, thanks to its precautionary procedure with very low human participation, ensuring that this footprint also captures the highest minute versions in the pattern.

b) Detection: To make future processing easier, the detection pipeline begins to change input images to Blob objects. The footprints are located by defining the classrooms and declaring a boundary box. For compatibility in deep learning, matrices are converted to a Numpy format. To provide predictions, the model examines the network and removes the teams that are important. Before scaling to keep things consistent, entrance images are annotated, transforms from BGR to RGB, masked to pay attention to footprints and along with the right annotation. Inclusion of changes in randomization, rotation and detection models increases its general identity accuracy by introducing diversity that allows it to adapt to the angles and background with different views and backgrounds.

iii) Algorithms:

To succeed in classifying animal footprints, use deep remaining learning to ignore the disappearance problems of the **resnet50** Deep Networks. Even in challenging environmental conditions, it can accurately identify the pattern thanks to your hierarchical feature learning. For applications associated with classification of wildlife images, the Resnet50 is an excellent alternative, as it guarantees fast training and increases generalization by neglecting data using shortcut connections. Both are contributed to the

ability to handle high -dimensional data [9] to both the recognition systems and increase the strength of the model in references from the real world.

InceptionResNetV2 residual connections and start-up modules help, resnetv2 can learn detailed descriptions from animal footprints, even the most complex people. This design improves classification accuracy by effectively gathering relevant and geographical information. Due to its several levels, it can be compatible with a variety of footprint forms and textures, making it a good fit for ecological research that includes minor changes in the footsteps and for the monitoring of wildlife [10].

With **DenseNet**, the footprint classification is transported to the next level by maximizing information and shield stream through close connection between layers. Model efficiency, parameter reduction and functions are all better than this connection. When it comes to visually similar classes, DenseNet actually shines in learning the fine properties of the animal footprint, making it a malignant competitor. The ability to achieve complete convenience representation enables accurately and extensible application for tracking wildlife in different surroundings [11].

When it comes to classification of real -time animals, **MobileNet** shines due to its mild and effective performance, which is perfect for built -in and mobile systems. Treatment classification decreases without sacrificing accuracy, thanks to its separate separation. Installations in the field in remote wildlife with low calculation resources are ideal for mobile. For conservation technologies that need to identify animal tracks quickly and accurately, speed compatibility is perfect [12].

To improve the efficiency and accuracy of the model in image classification features, the X uses separate separation from the depth. **Xception** enables classification of high -reduced species by capturing a slight difference in footprint symptoms when it comes to footprint analysis. Organic studies that require accurate trace recognition in various natural environments can benefit from architecture, which improves generalization on complex data sets and reduces overfitting [13].

A small for classification of **NasNetMobile** footprints gives a powerful model yet; It is ready for mobile efficiency and is designed through nerve architecture searches. This algorithm is perfect for field -cut wildlife monitoring units, as it maintains accuracy by reducing the calculation effort. By classifying strong data and providing assistance to automated organic surveillance systems, NasNetMobile performs well on a wide range of environmental conditions and footprint types [14].

Xception and NasNetMobile, when used together, improves the classification of the animal's footprint by combining the best characteristics of both architecture. The strength of this outfit technique is increased in several data sets and settings, by integrating its convenience exemption ability and the strength of prediction. In a complex environment with separate lights or topography, it improves the normalization by reducing the effect of individual model defects. In real -time applications, animal tracking applications are supported of continuous results, increasing the accuracy of footprints [15].

The **Yolov5x6** attacks a great blend between better architectural speed and accuracy, so it can stand out in detection of real -time animal footprints. The automatic monitoring system benefits from the exact identification and location functions of the

4. RESULTS AND DISCUSSION

footprint in the huge images. The ability to identify Yolov5x6 on multiple parameters allows effective detection of footprints with levels of different sizes and clarity. It helps to use footprint photography with non-invasive wildlife tracking and has rapid estimation functions, both of which are useful for large-scale organic monitoring. [14].

The **Yolov5S6** provides a small and effective way to find animal footprints, which is very good for places with small resources. It is well suited for distribution on the edge of the field monitoring system due to the rapid process and reliable detection accuracy. In mobile organic applications, where rapid detection is important for real-time analysis and quick collection data, Yolov5S6 effectively identifies the footprints in the difficult background. [11].

Efficient and quick detection of animal footprints with low hardware requirements are made possible by a mild architecture of **Yolov8n**. Exact ecosystems rely on its excellent performance by identifying small or partially visible footprints. Continuous monitoring of animal movements in different ecosystems and increases the real-time detection opportunities in protective and biological diversity studies, balancing performance with the Yolov8N speed [18].

Yolov9n offers state performance on the state-of-the-art object detection, with its condition-of-the-art adaptation for maximum accuracy and durability. Even under difficult conditions, for example in uneven terrain or with partial obstacles, it can accurately identify animal prints. The Yolov9n is perfect for academics and protectionists who need reliable footprint identity equipment for residential studies and tracking of wildlife because it has advanced architectural improvement that increases the reliability of identity [19] [20].



Fig.2 Home Page

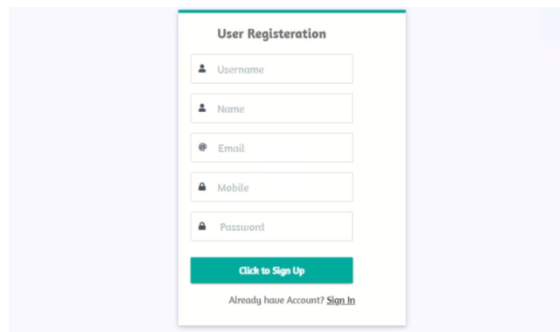


Fig.3 Registration Page

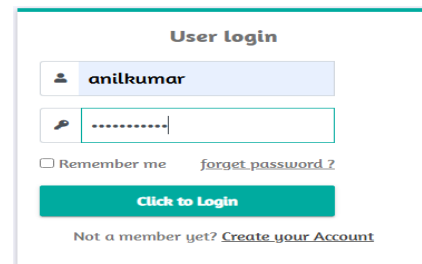


Fig.4 Login Page

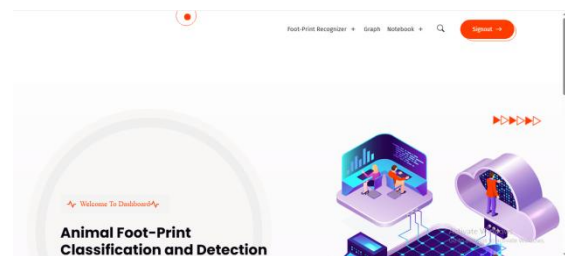


Fig.5 Main Page

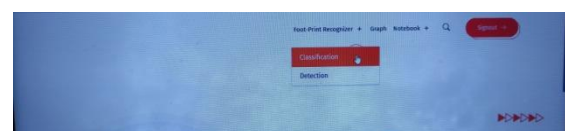


Fig.6 Classification



Fig.7 Upload Input Image



Fig.8 Final Outcome

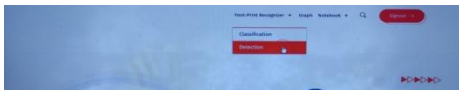


Fig.9 Detection



Fig.10 Upload Input Image



Fig.11 Predict Result

5. CONCLUSION

Finally, the proposed technique proves that sophisticated deep teaching models can accurately identify and classify animal prints. When it came to

classification, the enchanted model that included both “Xception and Nasnetmobile” performed best. This model provided more accurate and flexible classification of footprints than any other algorithm, which was examined. Compared to using the model alone, this attire method improves classification accuracy by redeeming complementary properties to two models. The best method for detecting footprints was the Yolov9N, which is perfect for real-time applications due to the high processing speed and pinpoint. The impressive performance of “Xception + Nasnetmobile and Yolov5x6” highlighted the promising applications of these deep teaching algorithms during ecological research and animal monitoring. Depending on the findings, these models have the ability to automate the process of identifying and detecting animal footprints, which may greatly benefit the environmental protection efforts.

Using with multiple topology and Hyperpieme setting to increase accuracy may be focused on future studies to limit and limit the classification models. The diversity of dataset when it comes to animal species and footprint types can improve the flexibility of the model. Additional performance benefits can be achieved by checking transfer learning and adjusting pre-informed models for special conditions. The purpose and efficiency of the model can be adapted to the function of real-time.

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