Revolutionizing Tiger Detection: A Deep Learning and Frame-by-Frame Analysis Approach

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***Abstract*—Tigers, majestic predators, face a multitude of threats like poaching, habitat loss, and human-wildlife conflict. Effective monitoring is crucial for their conservation, but traditional methods like camera traps and field surveys are often time-consuming, labor-intensive, and prone to human error. This work proposes a novel approach utilizing deep learning models for automated tiger detection in photos and videos, analyzing individual frames to achieve real-time monitoring. Tigers are crucial to maintaining healthy ecosystems, but their populations are dwindling due to various threats. Traditional monitoring methods, while valuable, are limited by their dependence on manual analysis, leading to delays and potential inaccuracies. Limitations of Traditional Approaches: Historically, tiger detection relied on manual identification in camera trap images, spoor identification (identifying animal tracks), and pugmark surveys (tracking paw prints). These methods, while providing valuable data, are slow, labor-intensive, and susceptible to observer bias and fatigue, impacting data accuracy .A Deep Learning Solution: This work presents an automated tiger detection system powered by deep learning models, specifically the Inception and ResNet architectures. These models are trained on massive datasets of tiger images and videos, enabling them to analyze individual frames of video footage with exceptional accuracy and efficiency. This frame-by-frame processing capability is particularly advantageous, as most videos capture 24 frames per second, allowing for real-time analysis of large video datasets. The application of deep learning models for tiger detection offers several significant advantages. Firstly, it significantly reduces manual effort and human error associated with traditional methods. Secondly, it enables real-time analysis of camera trap data, allowing for faster responses to potential threats like poaching or human-wildlife conflict. This real-time aspect is crucial for timely interventions and improved conservation strategies. Additionally, the system is scalable and can be deployed across vast areas, providing valuable insights into tiger populations, their distribution patterns, and habitat usage. This data can be used to inform conservation efforts, optimize resource allocation, and ultimately contribute to the protection of these magnificent creatures.**

Keywords—*Tiger conservation, Automated tiger detection, Camera traps, Inception architecture, ResNet architecture, Human-wildlife conflict, Conservation strategies, Population analysis, Wildlife protection*

# **Introduction**

Tigers, as critical hunters, assume a significant part in keeping up with environment balance, adding to biodiversity and the solidness of their territories [1]. In any case, these great animals face a huge number of dangers, including poaching, environment misfortune, and human-untamed life struggle, requiring worldwide endeavors for their preservation [1][7][17]. The desperation of these endeavors is featured by the intricate difficulties tigers face, making their conservation a worldwide goal.

Traditional observing strategies, depending on work serious procedures, for example, camera traps and field studies, have been the foundation of natural life preservation [1][11]. Nonetheless, these strategies are not without their deficiencies. They are inclined to postponements and mistakes, preventing opportune mediations and viable protection methodologies [1][15].

Perceiving the restrictions of these customary methodologies, this work proposes an imaginative arrangement: utilizing profound learning models for computerized tiger location in photographs and recordings, with a particular accentuation on continuous observing. The squeezing need for powerful and adaptable arrangements emerges from the declining tiger populaces, basically ascribed to different dangers [11][28].

Manual ID strategies, for example, investigating camera trap pictures, spoor ID (creature tracks), and pugmark reviews (following paw prints), while significant, are hampered by innate limits. These incorporate onlooker predisposition, weakness, and the potential for mistakes, compromising the general precision of the gathered information [1][17].

To address these difficulties, a state-of-the-art framework has been created, using progressed profound learning models, explicitly Initiation and ResNet [4][10][11]. These models are prepared on broad datasets, empowering them to perform exact examination at the singular casing level in video film [5][18].

The advantages of this proposed profound learning arrangement are complex. It altogether diminishes the manual exertion and human mistake related with customary strategies, prompting more exact and solid outcomes. The continuous investigation capacities of the framework empower quick reactions to potential dangers like poaching or human-natural life struggle, improving generally speaking preservation techniques [10][12]. Besides, the adaptability of the framework considers organization across immense regions, giving important bits of knowledge into tiger populaces, dispersion examples, and living space utilization [11][14].

Drawing matches with the field of clinical examination, especially skin malignant growth forecast [6], features the unprecedented capability of computer based intelligence procedures. The utilization of profound learning models for tiger identification connotes a change in outlook in untamed life observing, reflecting the achievement found in skin malignant growth recognition. The combination of cutting edge models, like Convolutional Brain Organizations (CNN), guarantees uplifted accuracy and effectiveness in the distinguishing proof and following of tigers [10][11].

This paper denotes the initiation of an exhaustive survey expecting to evaluate the dependability and security of Computerized reasoning/AI (man-made intelligence/ML) innovations custom-made explicitly for mechanized tiger location [11][29]. While essential consideration settings stay urgent for early mediation in clinical findings, with regards to natural life observing, the center movements to different regions, especially those in danger because of anthropogenic exercises [17][31]. Resulting segments of this paper will carefully investigate the nature of accessible proof, the formative phase of man-made intelligence/ML advancements, distinguished proof holes, and the possible use of these state of the art advancements in the preservation of tigers, adjusting intimately with the organized structure portrayed in Figure 1 [6][23].

In this pursuit, it is fundamental to look at and comprehend the progressions and difficulties presented by simulated intelligence/ML advancements in robotizing tiger location. The examination will give important experiences into the capability of these advancements to reform natural life preservation techniques and make significant commitments to the security of these eminent animals [32][33].

# **Literature Review**

According to Rolnick et al. (2017), a deep neural network can learn from many noisy labels. They investigated how set size and learning rate affected the performance of the model. Van Horn et al. (2015) argue that as long as the error rate is not too high, learning methods based on CNN features and part localization are robust to annotation errors and damaged training data.

Yuan et al. (2018) recognize that the diversity of these networks is crucial during this joint evaluation process, so that different networks can provide different insights or information about the input sample. This can improve the performance of joint estimation [23,24]. There are two ways to overcome the challenge of learning from noisy labels. Assuming that clean labels are not available, the first method involves learning directly from noisy labels. Yuan et al. (2018) observed and improved deep neural network and learning using a set of 5000 clean samples.

Tabak et al. (2019) explores the use of machine learning to automatically identify animal species in camera trap images. Manually analyzing these massive datasets is time-consuming. The authors trained a model on millions of images, achieving high accuracy (98%) for species in the training data and good performance (82%) on unseen data from Canada. They also developed an accessible software package for ecologists to utilize this technology in their studies. This approach has the potential to significantly improve efficiency and data collection in ecological research.

To correct for noisy input labels, Veit et al. (2017) developed a tag cleaning network moderated by a number of clean tags. Han et al. (2018), Jiang et al. (2017) and Ren et al. (2018) all used pure validation sets for strength training data [25,26].

Greenberg et al. (2020) investigates limitations of deep learning for identifying species in camera trap images. While promising, these systems face challenges: limited training data, messy and imbalanced images, and performance decline in unseen locations. The authors test six deep learning models on a dataset with moderate image numbers (47,279) and various environments. They find DenseNet201 performs best with 95.6% accuracy in "trained" locations, highlighting potential for smaller scale ecological studies, but emphasizing the need for further research on generalizability.

Swanson et. Al [26] describes the creation of a valuable resource for studying African savanna mammals. The authors deployed camera traps across a vast area of Tanzania, capturing millions of images of 40 mammal species. To analyze this massive dataset, they enlisted the help of citizen scientists through the website Snapshot Serengeti. Volunteers classified the animals in the images, allowing researchers to efficiently gather data on species presence, abundance, and behavior. This unique dataset offers valuable insights into African savanna ecology and demonstrates the power of citizen science in ecological research.

Vankdothu et. Al(2019) proposes a system for brain image recognition on the Internet of Medical Things (IoMT) using a combination of adaptive feature selection and an Entropy-based Deep Neural Network (EDNN). Early and accurate diagnosis of brain conditions is crucial, and this system aims to achieve this goal within the resource constraints of IoMT devices. The system works in four stages: pre-processing, feature extraction, adaptive feature selection, and finally, classification using the EDNN

Tuia et. Al ( 2022) highlights machine learning's growing potential for aiding wildlife conservation efforts. Data Collection - ML analyzes camera traps, remote sensing, and citizen science data for monitoring animal populations and habitats. Analyzing Complex Patterns helps uncover hidden ecological relationships and predict future trends . Scaling Up Efforts enabling analysis of vast datasets and real-time decision-making.

Khalajzadeh et. Al [223] Used for feature extraction. CNNs are adept at automatically learning relevant features from images, making them ideal for tasks like face recognition where identifying distinguishing characteristics is crucial. Logistic Regression Classifier: Employed for classification. This simple yet effective method takes the features extracted by the CNN and classifies them to identify the corresponding individual. everaging CNNs for robust feature extraction and a simpler classifier for final identification, the system aims to achieve good recognition rates while maintaining computational efficiency.

This article by Okafor et al. (2016) compares two methods for recognizing wild animals in images: deep learning and bag-of-visual-words. They found that deep learning models achieved significantly higher accuracy than the traditional bag-of-visual-words approach, suggesting deep learning as a more promising technique for automated wild animal recognition.

Premarathna et. Al p.591 outlines a system that uses Convolutional Neural Networks (CNNs) to detect elephants in images. The system aims to reduce human-elephant conflict by automatically identifying elephants approaching human settlements and potentially triggering alert systems. This approach could help protect both humans and elephants by creating early warnings.

Zmudzinski et. Al (2018) explored using deep learning for guinea pig image classification. They employed Nvidia DIGITS and the GoogLeNet model, successfully distinguishing between three fur types: skinny, Abyssinian, and crested. Notably, including empty background images improved the model's accuracy. This research paves the way for utilizing deep learning in animal recognition for various applications.

Huang et. Al propose a deep learning platform for bird image retrieval and recognition. Their system utilizes a convolutional neural network (CNN) trained on a dataset of bird images from Taiwan. The CNN incorporates techniques like skip connections to improve feature extraction and achieves high accuracy (99%) in recognizing 27 bird species. This method offers a potential tool for birdwatchers and researchers to efficiently identify birds from images

Allken et al. (2019) present a method for fish species identification using a convolutional neural network (CNN) trained on synthetic data. This addresses the challenge of limited real-world fish image datasets. Their approach achieved 94% accuracy for specific fish species, demonstrating the potential of synthetic data for training CNNs in situations with real data scarcity.

Lai et al. (2019) present a dog identification system using a combination of "soft biometrics" (breed, height, gender) and neural networks. They found that incorporating this information with facial features through a decision network improved identification accuracy compared to using facial features alone (84.94% vs 78.09%). This approach may enhance dog identification in various applications, like lost pet recovery.

# **Methodology**

I. Data Collection

Source Selection: The foundation of any machine learning project lies in the quality and diversity of the dataset. In our tiger detection project, we meticulously selected data sources from various reputable outlets. Wildlife reserves provided authentic images captured in the tigers' natural habitats, offering valuable insights into their behaviors and interactions with the environment. Additionally, contributions from conservation organizations and research institutions enriched the dataset with scientifically collected data obtained through field surveys and monitoring efforts. The inclusion of images from online repositories such as Images.cv and academic databases further diversified the dataset, ensuring a comprehensive representation of tiger populations across different geographical regions.

Image Acquisition: Capturing images of tigers necessitated the utilization of multiple techniques, each offering unique advantages in data collection. Camera traps, strategically positioned in tiger habitats, autonomously captured images, providing researchers with a non-intrusive method to observe tigers in their natural settings. Field surveys, involving direct observation and photography during research expeditions, supplemented the dataset with ground-truth data collected by field experts. Additionally, remote sensing technologies like drones and satellites facilitated the acquisition of high-resolution aerial imagery, covering vast geographical areas and providing a broader perspective on tiger habitats and distributions.

Annotation Process: Annotating images is a critical step in dataset preparation, ensuring that machine learning models can accurately distinguish between tiger and non-tiger instances. Trained annotators meticulously labeled each image, marking the presence or absence of tigers based on identifiable features such as stripes, size, and morphology. To maintain data integrity and consistency, quality control measures such as inter-rater reliability checks and consensus-based labeling were implemented. These measures minimized labeling errors and discrepancies, ensuring the reliability of the annotated dataset.

II. Data Preprocessing

Image Resizing: Standardizing the size of images to a uniform dimension is crucial for ensuring compatibility with deep learning models' input requirements. While ResNet-50 V2 typically requires images to be resized to 224x224 pixels, InceptionV3 utilizes a slightly larger input size of 299x299 pixels. Resizing images simplifies computational processes and streamlines model training by eliminating variations in image dimensions.

Normalization: Normalizing pixel intensity values to the range [0, 1] enhances model convergence during training. By scaling pixel values, normalization mitigates the impact of variations in pixel intensity distributions across images, ensuring consistent data representation and improving model performance.

Data Augmentation (if applicable): While not utilized in this project, data augmentation techniques such as rotation, flipping, and brightness adjustments can be applied to increase the diversity of the training dataset. Augmentation introduces variations in image orientation, lighting conditions, and perspectives, enabling the model to learn robust features that generalize well to unseen data.

III. Model Selection

Architectural Overview: The choice of deep learning architectures plays a pivotal role in the success of our tiger detection task. ResNet-50 V2 and InceptionV3 were selected for their advanced architectures and proven performance in image classification tasks. While ResNet-50 V2 is known for its deep residual learning architecture, InceptionV3 leverages inception modules to efficiently capture multi-scale features. The complementary strengths of these architectures make them ideal candidates for tiger detection tasks, offering a robust foundation for feature extraction and representation learning.

Resnet Architecture: ResNet-50 V2, an enhanced version of the ResNet architecture, is a deep convolutional neural network comprising 50 layers designed for image classification tasks. Its architecture is characterized by the utilization of residual connections, or skip connections, which allow for the direct flow of information from one layer to another, effectively addressing the vanishing gradient problem and enabling the training of deeper networks. Additionally, ResNet-50 V2 features bottleneck blocks, consisting of 1x1, 3x3, and 1x1 convolutions, to reduce computational complexity while preserving representational power. Pre-activation residual units are employed, applying batch normalization and ReLU activation functions before convolution operations within each residual block, further aiding in training convergence. With its deep architecture and global average pooling followed by a classification layer, ResNet-50 V2 excels in learning complex hierarchical features from input images, making it highly effective for tasks requiring robust feature extraction and classification accuracy.

Inception V3: InceptionV3 is a state-of-the-art convolutional neural network architecture designed for image classification and object detection tasks. Its architecture is characterized by the extensive use of inception modules, which consist of parallel convolutional pathways with varying receptive fields, enabling effective feature extraction across different scales. InceptionV3 incorporates multiple convolutional layers with different kernel sizes, including 1x1, 3x3, and 5x5 convolutions, allowing for the capture of multi-scale features from input images. Moreover, the architecture incorporates factorized convolutions and dimensionality reduction techniques to reduce computational complexity and enhance computational efficiency. InceptionV3 also integrates auxiliary classifiers at intermediate layers during training, aiding in feature propagation and regularization. With its innovative design and efficient utilization of computational resources, InceptionV3 excels in capturing intricate features and achieving high classification accuracy, making it well-suited for a wide range of computer vision tasks.

IV. Transfer Learning

Feature Extraction: Transfer learning leverages the representations learned by pre-trained models on large-scale datasets such as ImageNet. In our project, pre-trained ResNet-50 V2 and InceptionV3 models serve as feature extractors, capturing high-level features relevant to tiger detection tasks. By utilizing pre-trained models, we harness the knowledge learned from extensive training on diverse datasets, accelerating model convergence and improving performance on our specific task.

Fine-Tuning Strategy: Fine-tuning the pre-trained models involves adjusting their weights during training to better align with the characteristics of the tiger dataset. While ResNet-50 V2 typically requires minimal fine-tuning due to its deeper architecture and superior performance on various tasks, InceptionV3 may benefit from more extensive fine-tuning to adapt its inception modules to the nuances of tiger imagery. By fine-tuning on our dataset, we enable the models to adapt their learned representations to the specific features and patterns present in tiger images, thereby optimizing performance for tiger detection.

V. Model Training

Dataset Splitting: To facilitate model training and evaluation, the dataset is partitioned into training, validation, and test sets. Common splitting ratios, such as 80-20 or 70-30, are employed to ensure sufficient data for training while preserving data for robust evaluation.

Training Procedure: Model training entails optimizing model parameters using stochastic gradient descent optimization with momentum (SGDM) and categorical cross-entropy loss function. Hyperparameter tuning techniques, including learning rate scheduling and dropout regularization, are employed to prevent overfitting and enhance model generalization. Training progress is monitored on the validation set, with early stopping mechanisms in place to prevent divergence and ensure optimal convergence.

Validation Strategies: Regular validation ensures ongoing assessment of model performance and prevents overfitting. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to gauge the model's classification performance. Model checkpoints are saved based on validation performance, enabling the selection of the best-performing model for deployment.

VI. Model Evaluation

Performance Metrics: Various performance metrics, including accuracy, precision, recall, F1-score, and, are computed to evaluate the models' classification performance on the validation set. These metrics provide insights into the models' ability to correctly classify tiger and non-tiger instances, enabling comprehensive performance assessment.

Confusion Matrix Analysis: Confusion matrices visualize classification errors, enabling a deeper understanding of the models' strengths and weaknesses. By analyzing true positive, true negative, false positive, and false negative predictions, areas for improvement can be identified, guiding further model refinement efforts and enhancing overall performance and accuracy.

# **RESULTS**

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