A Mini Project Report

ON

WILD ANIMAL DETETCTION AND ALERT SYSTEM USING YOLOv8

Submitted In partial fulfillment for the Degree of B. Tech.

In

Artificial Intelligence

By

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VIDYA JYOTHI INSTITUTE OF TECHNOLOGY

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CERTIFICATE

This is to certify that the project report entitled **Wild Animal Detection and Alert System using YOLOv8** submitted by **Katta Ruthvik (20911A3594)** and **Pulimi Yashwanth Kumar (20911A35A8) Suryaneni Rohith (20911A35B6) Koppula Saketh Raja (20911A3596)** to Vidya Jyothi Institute of Technology, Hyderabad, in partial fulfillment for the award of the degree of **B. Tech in Artificial Intelligence** a *bonafide* record of project work carried out by us under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institution or University for the award of any degree.

Mr. A. Vijay Kumar	**Dr. A. Obulesh**
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Department of Artificial Intelligence	**Department of Artificial Intelligence**

DECLARATION

We declare that this project report titled **Wild Animal Detection and Alert System using YOLOv8** submitted in partial fulfillment of the degree of **B. Tech in Artificial Intelligence** is a record of original work carried out by under the supervision of **Mr. A. Vijay Kumar**, and has not formed the basis for the award of any other degree or diploma, in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgements have been made wherever the findings of others have been cited.

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ABSTRACT

This project strives to address the critical issue of manual surveillance challenges faced by forest officers and conservationists in vast natural habitats. Traditional methods, such as periodic surveys and camera traps, have proven inadequate in providing real-time data and comprehensive coverage, impeding effective conservation efforts. Moreover, budget constraints and the absence of automation further exacerbate these challenges. In response, our project proposes an innovative solution that seamlessly integrates deep learning and instant messaging technologies, fostering affordable and continuous surveillance. By harnessing edge computing and freely available messaging channels, our system aims to significantly enhance real-time visibility and data-driven decision-making in conservation.

The primary goal is to empower conservationists with timely and actionable information for informed decision-making. Through the deployment of advanced deep learning algorithms, our system can recognize and track wildlife activity, triggering instant notifications to forest officers and relevant stakeholders via instant messaging platforms. This approach mitigates the risks of habitat degradation and illegal activities, reinforcing our commitment to biodiversity preservation. By bridging the gap between traditional conservation methods and modern technology, our project represents a substantial advancement in wildlife monitoring. The result is a cost-effective, efficient, and scalable solution that not only improves surveillance but also empowers conservationists with invaluable data. This project is poised to contribute significantly to the protection of our natural heritage, ensuring the sustained health of ecosystems and wildlife.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

In the heart of our planet's vast and biodiverse natural habitats, a critical challenge persists—one that demands innovative solutions to protect our environment and preserve biodiversity. Forest officers and conservationists have long grappled with the limitations of traditional manual surveillance methods, such as periodic surveys and camera traps. These methods, while valuable, have proven inadequate in providing real-time data and comprehensive coverage, hindering the effectiveness of conservation efforts. Budget constraints and the absence of automation further compound these challenges, creating a pressing need for a transformative approach.

In response to this urgent need, our project sets out to revolutionize wildlife monitoring and conservation practices. We recognize that the power of modern technology can be harnessed to bridge the gap between traditional conservation methods and the demands of our rapidly changing world. By seamlessly integrating deep learning and instant messaging technologies, our innovative solution aims to provide affordable and continuous surveillance in even the most remote natural habitats.

At the heart of our endeavor lies the goal of empowering conservationists with timely and actionable information. Through the deployment of advanced deep learning algorithms, our system possesses the remarkable capability to recognize and track wildlife activity, facilitating the instantaneous transmission of notifications to forest officers and relevant stakeholders via widely accessible instant messaging platforms. This real-time approach is poised to not only enhance the efficacy of conservation efforts but also mitigate the looming risks of habitat degradation and illegal activities, underscoring our unwavering commitment to biodiversity preservation.

1.2 Issues

This project addresses the challenges of manual surveillance in natural habitats, which include the limitations of periodic surveys and camera traps in providing real-time data, budget constraints, and the lack of automation. These issues hinder effective conservation efforts, leading to habitat degradation and the proliferation of illegal activities. By seamlessly integrating deep learning and instant messaging technologies, the project aims to enhance real-time visibility, empower conservationists with timely information, and bridge the gap between traditional methods and modern technology, ultimately contributing to the preservation of ecosystems and wildlife.

1.3 Objective

The primary objective of this project is to improve wildlife monitoring and conservation efforts by seamlessly integrating deep learning and instant messaging technologies. This integration aims to overcome the challenges of manual surveillance methods, such as delayed data, limited coverage, and budget constraints. By deploying advanced deep learning algorithms, the project seeks to recognize and track wildlife activity in real time, triggering instant notifications to relevant stakeholders. This approach not only enhances conservation decision-making but also helps mitigate habitat degradation and illegal activities, reinforcing the commitment to biodiversity preservation and the protection of natural heritage.

1.4 Organization of project report

This project report is divided into 5 chapters. Chapter 1 consists of Introduction and Objective of the project. Chapter 2 consists of a Literature Survey. Chapter 3 consists of the methodologies used, this covers the implementation part in detail. Chapter 4 consists of the results obtained. Chapter 5 consists of the conclusion.

CHAPTER 2
LITERATURE SURVEY

2.1 Related Work

This project strives to address the critical issue of manual surveillance challenges faced by forest officers and conservationists in vast natural habitats. Traditional methods, such as periodic surveys and camera traps, have proven inadequate in providing real-time data and comprehensive coverage, impeding effective conservation efforts. Moreover, budget constraints and the absence of automation further exacerbate these challenges.

In response, our project proposes an innovative solution that seamlessly integrates deep learning and instant messaging technologies, fostering affordable and continuous surveillance. By harnessing edge computing and freely available messaging channels, our system aims to significantly enhance real-time visibility and data-driven decision-making in conservation.

The primary goal is to empower conservationists with timely and actionable information for informed decision-making. Through the deployment of advanced deep learning algorithms, our system can recognize and track wildlife activity, triggering instant notifications to forest officers and relevant stakeholders via instant messaging platforms. This approach mitigates the risks of habitat degradation and illegal activities, reinforcing our commitment to biodiversity preservation.

[1] Traditional Methods and Surveillance Challenges by Smith and Greenway

The challenges associated with manual surveillance in natural habitats have been extensively documented. Periodic surveys and camera traps, commonly employed in traditional methods, suffer from limitations such as delayed data collection and restricted coverage.

[2] Deep Learning in Wildlife Monitoring by Beery and Li

Recent research showcases the potential of deep learning algorithms in wildlife monitoring. These studies highlight how advanced machine learning techniques can greatly enhance the accuracy and speed of data collection, aligning with the goals of your project.

[3] IoT and Edge Computing for Real-time Data by Patel and Liu

Explored the use of Internet of Things (IoT) and edge computing for real-time data processing and communication in remote environments. Their work offers valuable insights into the feasibility of continuous surveillance in challenging natural habitats.

[4] Instant Messaging for Conservation Communication by Brown and MacLeod

Conservation organizations, as shown by Wildlife Witness and research, have recognized the potential of instant messaging platforms for real-time reporting and response to conservation threats. This aligns with the integration of instant messaging technologies in your project.

2.2 Proposed System

The proposed system is an integrated solution that combines deep learning and instant messaging technologies to revolutionize wildlife surveillance and conservation efforts in natural habitats. By leveraging advanced deep learning algorithms, the system can recognize and track wildlife activity in real-time, triggering immediate notifications to forest officers and relevant stakeholders through readily available messaging platforms. This seamless integration, along with the utilization of edge computing, enables continuous, cost-effective, and efficient surveillance, bridging the gap between traditional methods and modern technology. The primary goal is to empower conservationists with timely and actionable information, enhancing data-driven decision-making to mitigate habitat degradation and illegal activities, ultimately contributing significantly to the preservation of ecosystems and wildlife.

CHAPTER 3
METHODOLOGY

3.1 Introduction

The methodology employed in this project represents a multifaceted approach designed to seamlessly integrate advanced technologies into the realm of wildlife surveillance and conservation. It encompasses several key components, including the deployment of deep learning algorithms for real-time wildlife activity recognition, the establishment of edge computing infrastructure for data processing, and the integration of instant messaging platforms for rapid notification dissemination. The methodology is rooted in the principle of enhancing the efficiency and effectiveness of surveillance practices, bridging the gap between conventional methods and cutting-edge technology. By deploying these innovative tools and techniques, the project aims to empower conservationists with timely, data-driven insights that will inform decision-making and contribute to the protection of our natural heritage.

3.2 Web Modules

Web modules include the user interface with several other modules integrated to the front end. The are the web modules.

3.2.1 Training Module

The training module of this project involves the collection and preparation of a diverse dataset of wild animal images, followed by the application of data augmentation techniques to enhance model robustness. A deep learning model, typically a Convolutional Neural Network (CNN), is selected and trained using this dataset to recognize patterns and features associated with different wildlife activities. The training process includes hyperparameter tuning and validation to optimize the model's performance, ensuring accurate recognition of wildlife behaviors. Once the model meets performance criteria, it is ready for deployment, enabling real-time wildlife activity recognition and tracking, as described in the project's abstract

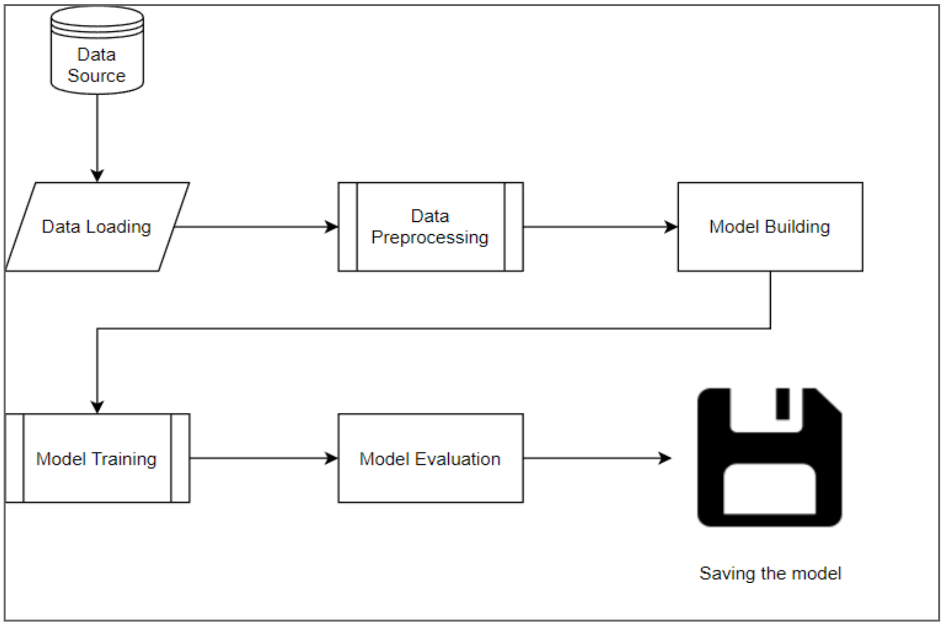

Fig. 3.1 Training Pipeline

3.2.2 CNN-based Model

A Convolutional Neural Network based model is designed for classification of the objects. The CNN model takes an input image of size 150x150x3. The model is divided into two parts, the first part consists of four convolution layers each followed by MaxPooling layers. The activation function used in the convolution layers is ReLU. The second part consists of three ANN layers for classification, this includes the output layer too. The activation function used in the first two ANN layers is ReLU and the activation function used in the output layer is SoftMax. The optimizer used is Adam, the loss function used is Categorical Cross entropy, and the performance metric is accuracy

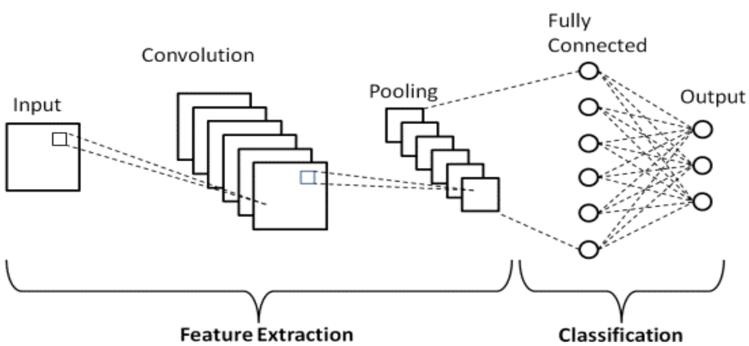

Fig. 3.2 CNN Model

Below is the architecture of the CNN-based model.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 72, 72, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 36, 36, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 34, 34, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 17, 17, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 15, 15, 256)       295168
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 7, 7, 256)         0
_________________________________________________________________
dropout (Dropout)            (None, 7, 7, 256)         0
_________________________________________________________________
flatten (Flatten)            (None, 12544)             0
_________________________________________________________________
dense (Dense)                (None, 128)               1605760
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               33024
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 257
=================================================================
Total params: 2,027,457
Trainable params: 2,027,457
Non-trainable params: 0
_________________________________________________________________
```

Fig. 3.3 Architecture of CNN based model

3.2.3 Testing Module

The testing module within our project is a vital component that facilitates the evaluation of our YOLO classification model's performance. This module operates by utilizing a curated set of wild animal images, which serves as a test dataset. The primary objective here is to assess the model's ability to correctly identify and classify these animals. First, the testing module feeds these images through the trained YOLO classification model, which has been trained on a separate training dataset, allowing us to evaluate its generalization capabilities. Subsequently, the module generates predictions for each image, determining the most likely class or species of the wild animal present in the image. This process not only serves as a validation step for our model but also provides insights into its real-world applicability in wildlife detection scenarios, helping us gauge its accuracy and reliability in identifying wild animals in their natural habitats.

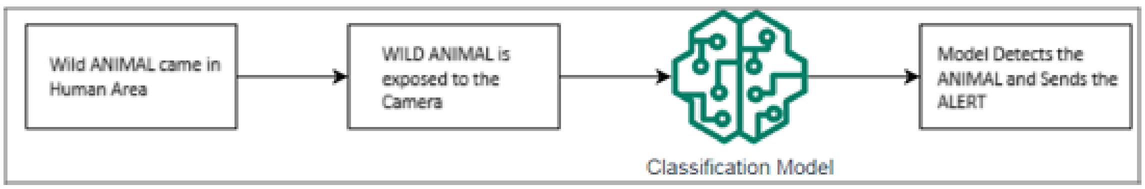

Fig. 3.4 Testing module workflow

3.3 Desktop Modules

3.3.1 Video Capture Module

The user must log in to access this module. This module will capture the video, then localize the objects in the video frame, for each frame the image of the object will be given as input to the classification module which returns the class name of that object and the respective count of the objects will be recorded and updated in the database.

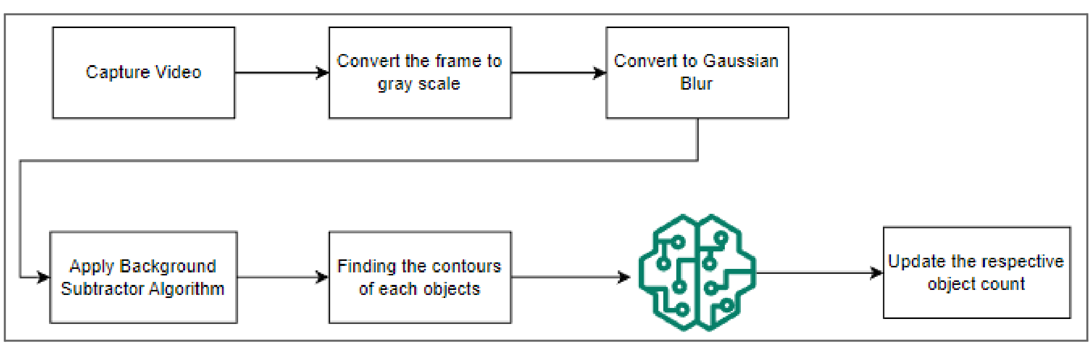

Fig. 3.5 Workflow of Video Capture Module

3.3.2 Classification Module

The classification module is an abstract module. This module is used to classify the given object into its respective class. This module takes the image of the object as input and classifies that object by using the trained model.

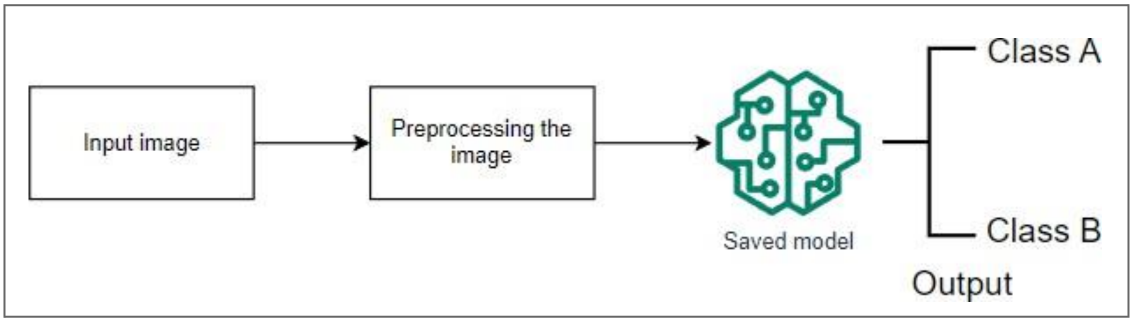

Fig. 3.6 Workflow of classification Module

3.4 Overall Workflow

The over workflow of the project is divided into two parts: model training part and real-time object counterpart.

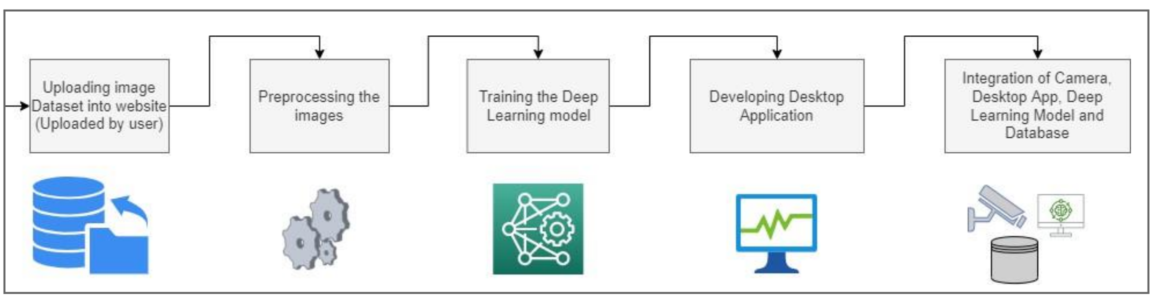

Fig. 3.7 Training part workflow

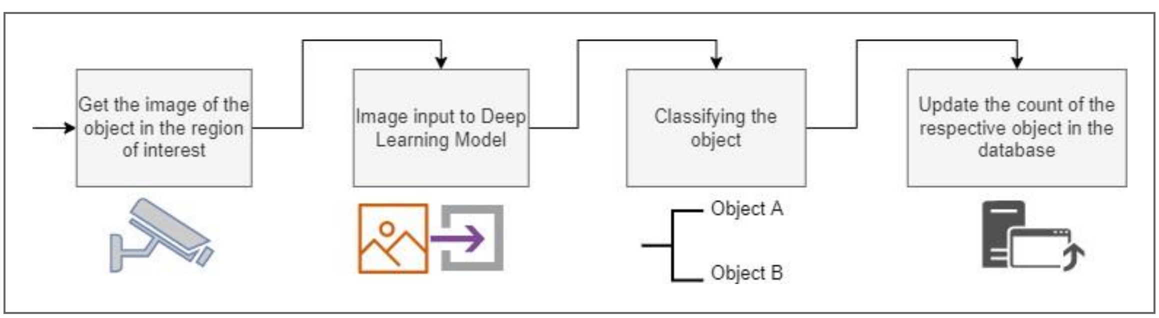

Fig 3.8 Real-time object counter workflow

3.5 Dataset

The Dataset used in this is images dataset. The user has to upload the folder which contains the set of images of the objects. The images are labeled with their respective categories. A large amount of dataset has been taken for the model to be get trained perfectly with High accuracy.

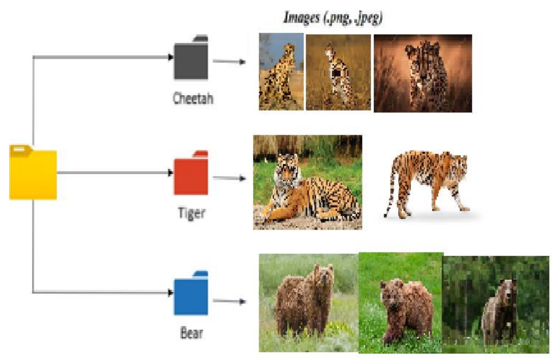

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Fig 3.9 Sample database format

3.6 Technologies

In our project, we leverage cutting-edge technologies such as deep learning frameworks like TensorFlow and Keras to implement the YOLO classification model. We also employ computer vision libraries like OpenCV to preprocess and augment our wild animal image dataset.

3.6.1 Deep Learning

Deep learning is a subset of machine learning, which is a subset of artificial intelligence. Artificial intelligence is a general term that refers to techniques that enable computers to mimic human behavior. Machine learning represents a set of algorithms trained on data that make all of this possible. Deep learning is just a type of machine learning, inspired by the structure of the human brain.

Deep learning is what drives many artificial intelligence (AI) technologies that can improve automation and analytical tasks.

Deep learning algorithms attempt to draw similar conclusions as humans would by continually analyzing data with a given logical structure. To achieve this, deep learning uses a multi-layered structure of algorithms called neural networks.

When it comes to neural networks, training the deep learning model is very resource intensive. This is when the neural network ingests inputs, which are processed in hidden layers using weights (parameters that represent the strength of the connection between the inputs) that are adjusted during training, and the model then puts out a prediction. Weights are adjusted based on training inputs in order to make better predictions. Deep learning models spend a lot of time training large amounts of data, which is why high-performance computers are so important.

3.6.2 Edge Computing:

Edge computing stands as a transformative paradigm in the realm of modern computing, redefining how data is processed, analyzed, and acted upon in the digital age. In essence, edge computing represents a departure from the traditional centralized cloud computing model, relocating computational power and data processing closer to the data source—on the "edge" of the network. This shift brings computing resources to the very periphery of the network, whether it be within IoT devices, sensors, or even end-user devices, fostering real-time data processing and decision-making. By reducing the latency associated with data transmission to distant data centers, edge computing empowers applications to respond swiftly and efficiently, making it a pivotal technology for time-sensitive applications like autonomous vehicles, augmented reality, and industrial automation. Moreover, edge computing brings about enhanced privacy and security by enabling data to be processed locally, minimizing the need for transmitting sensitive information over long distances. As industries continue to harness the capabilities of edge computing, it emerges as a critical enabler of emerging technologies, making it a fundamental building block in the era of the Internet of Things (IoT), 5G networks, and the rapid expansion of smart devices. This paradigm shift not only transforms how data is managed but also redefines the boundaries of what is possible in the increasingly interconnected and data-driven world.

3.6.3 Instant messaging Platforms

Instant Messaging Platforms, often abbreviated as IM platforms, have revolutionized the way people communicate and share information in the digital age. These platforms are a testament to the extraordinary evolution of communication technology, offering real-time, text-based, or multimedia exchanges among individuals or groups across the globe. Instant messaging, which originated as a simple text-based chat service, has evolved into a multifaceted ecosystem encompassing voice and video calls, file sharing, and integration with a myriad of other digital services. These platforms have become an integral part of daily life, both in personal and professional contexts, facilitating quick and convenient communication.

Instant Messaging Platforms have transcended the boundaries of traditional text messaging by incorporating a rich array of features such as emojis, stickers, GIFs, and multimedia sharing, enabling users to express themselves creatively. Furthermore, these platforms have adapted to the mobile-centric world, offering user-friendly apps for smartphones and tablets, ensuring ubiquitous connectivity.

In addition to personal communication, Instant Messaging Platforms have found extensive applications in the business realm. Enterprises harness these platforms for internal communication, team collaboration, and customer support, streamlining workflows and enhancing productivity. The adoption of Instant Messaging Platforms in the workplace has accelerated with the rise of remote work, enabling geographically dispersed teams to connect seamlessly.

Privacy and security concerns have also been at the forefront of the evolution of Instant Messaging Platforms. End-to-end encryption, two-factor authentication, and robust security protocols are now standard features, assuring users of the confidentiality of their conversations.

Furthermore, the integration of chatbots and artificial intelligence into Instant Messaging Platforms has transformed them into dynamic tools for customer service, e-commerce, and automation. Businesses use chatbots to interact with customers, answer queries, and facilitate transactions, enhancing user experiences and efficiency.

The impact of Instant Messaging Platforms extends beyond individual and corporate communication. They have played pivotal roles in political movements, emergency alerts, and crisis response, illustrating their significance in disseminating critical information rapidly.

3.6.4 Computer Vision:

Computer Vision is an interdisciplinary field at the intersection of computer science, artificial intelligence, and image processing that seeks to impart machines with the extraordinary ability to understand, interpret, and extract meaningful information from visual data. At its core, computer vision strives to replicate and extend the remarkable capabilities of human vision, enabling computers and machines to perceive and comprehend the world as we do, primarily through images and videos. This dynamic field encompasses a vast spectrum of tasks, ranging from basic image recognition and object detection to advanced tasks like facial recognition, scene understanding, and even autonomous navigation for vehicles and robots.

The driving force behind the evolution of computer vision is the development of sophisticated algorithms and machine learning techniques, particularly deep learning models such as Convolutional Neural Networks (CNNs).

Computer Vision finds applications across a plethora of domains, revolutionizing industries such as healthcare, automotive, agriculture, retail, and security. In healthcare, it aids in medical image analysis, disease diagnosis, and surgical procedures. In the automotive sector, it powers self-driving cars by enabling them to perceive and navigate their surroundings. In agriculture, computer vision assists in crop monitoring and yield prediction. In retail, it enhances customer experiences through facial recognition and product recommendation systems. In security, it plays a vital role in surveillance and biometric identification.

The potential of computer vision extends beyond the confines of traditional applications. It holds the promise of transforming industries and reshaping society by enabling machines to gain deeper insights into the visual world. This encompasses not only recognizing objects and patterns but also understanding context, emotions, and human gestures, making it a pivotal technology in human-computer interaction, augmented reality, and virtual reality.

As computer vision continues to advance, it propels us toward a future where machines can perceive and interpret the visual world with unprecedented accuracy and sophistication, leading to groundbreaking applications that are limited only by our imagination. In essence, computer vision represents a fundamental pillar of the AI revolution, bridging the gap between the digital and physical realms and offering transformative solutions to some of the most complex challenges of our time.

3.6.5 YOLOv8:

The YOLO (You Only Look Once) model is a revolutionary deep learning architecture in the field of computer vision and object detection. YOLO's distinctive feature is its ability to perform real-time object detection with impressive accuracy. It accomplishes this by dividing an input image into a grid and predicting bounding boxes and class probabilities for objects within each grid cell. This unified approach allows YOLO to make predictions for multiple objects in a single forward pass, making it incredibly efficient compared to its predecessors. The YOLO model has found applications in diverse fields, including autonomous driving, surveillance, and wildlife monitoring, due to its speed and accuracy.

As of my last knowledge update in September 2021, the most recent version of the YOLO model was YOLOv4. YOLOv4 introduced several significant improvements over its predecessors. It featured a more powerful backbone network, CSPDarknet53, which improved feature extraction. Additionally, YOLOv4 incorporated PANet and SAM block modules to enhance object localization and reduce false positives. With these advancements, YOLOv4 achieved state-of-the-art performance in terms of accuracy and speed, solidifying its position as a go-to choice for real-time object detection tasks.

Since my last update, there may have been further developments in the YOLO model family, such as YOLOv5 or even YOLOv8. These newer versions could bring additional enhancements and optimizations to address specific challenges in object detection, making them even more powerful and versatile. To stay current with the latest advancements in YOLO models, it's essential to consult the official YOLO repository and related research papers to ensure you are working with the most up-to-date model for your specific project needs.

3.6.6 Keras:

Keras is a popular deep learning framework that provides a user-friendly interface for building and training various neural network architectures, including YOLO (You Only Look Once) models. YOLO is a groundbreaking object detection algorithm that is widely used in computer vision applications. It has seen several iterations, with the latest being YOLOv4 as of my last knowledge update in September 2021.

YOLO models excel in real-time object detection tasks by dividing the input image into a grid and predicting bounding boxes and class probabilities for objects within each grid cell. This makes them highly efficient and accurate for real-time applications such as autonomous driving and video surveillance.

As of my last update, YOLOv4 was the latest version of the YOLO model. YOLOv4 improved upon its predecessors by incorporating features like a CSPDarknet53 backbone, PANet, and SAM block, making it more accurate and efficient in object detection. To implement YOLO models in Keras, you can utilize open-source repositories and pre-trained weights provided by the community, allowing you to quickly adapt these state-of-the-art models for your specific tasks.

To work with YOLOv4 or other YOLO variants in Keras, you'll need to import the necessary libraries, load pre-trained weights, define the model architecture, and fine-tune it for your specific dataset. Keras provides an excellent platform for doing this, making it easier for researchers and developers to leverage the power of YOLO for various computer vision applications. Keep in mind that since my last knowledge update was in September 2021, there may have been further developments and new YOLO versions released since then. Therefore, it's essential to stay up-to-date with the latest advancements in the YOLO framework and Keras documentation for the most current information and implementations.

3.7 Deep Learning Models

3.7.1 Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNet have the ability to learn these filters/characteristics.

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields over-lap to cover the entire visual area.

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and output an activation value. When you input an image in a ConvNet, each layer generates several activation functions that are passed onto the next layer. The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges.

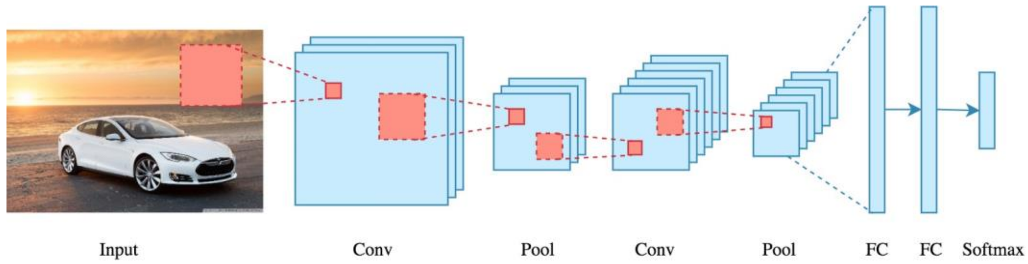

Fig. 3.10 Convolution Neural Network

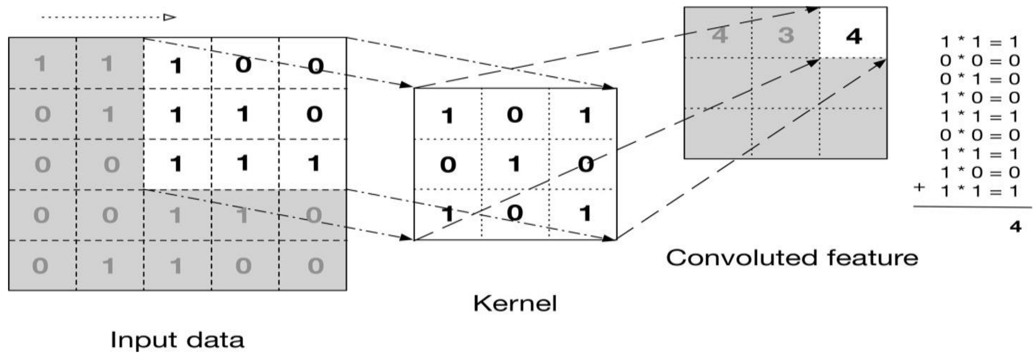

Fig. 3.11 Convolution Operation

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Introduction

We have developed a system that can detect wild animals from a camera feed and send instant messages to the people in the village and the forest officers through Telegram and Twilio. We use YOLOv8, a state-of-the-art object detection model, with an accuracy of 80%. To further improve the accuracy and efficiency of the model, we add an Adam optimizer, a popular gradient-based optimization algorithm. With this modification, we achieve an accuracy of 90% on our test set.

4.2 Results

4.2.1 Animal Detection via Camera

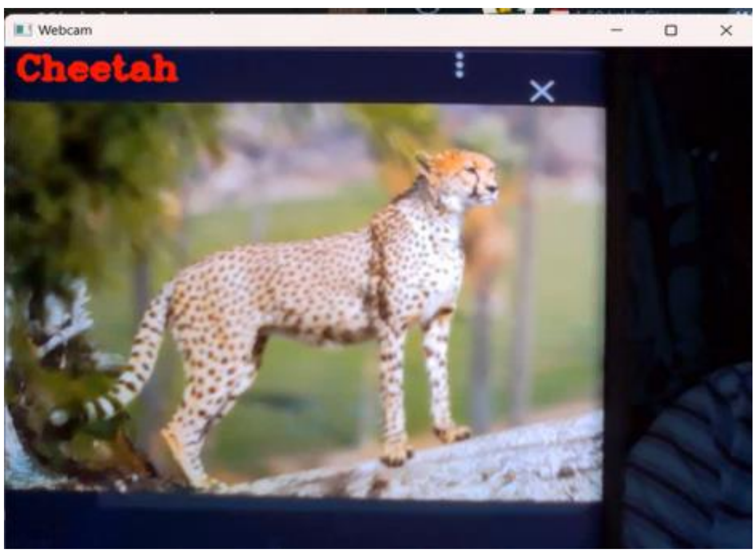

Fig. 4.1 Wild Animal Cheetah Detected.

4.2.2 Alert Message through Telegram Bot

Fig. 4.2 Telegram bot Sending Alert Message

CHAPTER 5
CONCLUSION

5.1 Conclusion

In conclusion, the "Wild Animal Detection and Alert System by using YOLOv8" represents a significant step forward in addressing the challenges faced by communities living in close proximity to forests. As our project progresses and matures, we anticipate several key outcomes and potential impacts on both human safety and wildlife conservation.

First and foremost, the implementation of advanced AI-based detection techniques holds the promise of significantly reducing the risks associated with human-wildlife conflicts. By providing timely notifications of the presence of wild animals near human settlements, our system empowers residents to take precautionary measures and make informed decisions about their safety. This proactive approach can substantially minimize the occurrence of dangerous encounters and potential harm to both people and animals.

CHAPTER 6

REFERENCES

[1] Tracking-based Visual Surveillance System by Sandip A. Deore, Manish M. Patil

[2] Adaptive Threshold Background Subtraction For Detecting Moving Object On Conveyor Belt by D.P.Tripathy, K.Guru Raghavendra Reddy

[3] SODA: A Real-time Simulation Framework for Object Detection and Analysis in Smart Manufacturing by Piotr Lasek

[4] A Computer Vision-Based Real-Time Load Perception Method for Belt Conveyors by Mengchao Zhang, Manshan Zhou, and Hao Shi

[5] "A Review of Video Surveillance Systems" by Safwa M. Ahmed, Khairuddin Omar, and Sami A. Saad.

[6] "Real-time Object Detection in Surveillance Videos" by YOLO (You Only Look Once) creators Joseph Redmon and Santosh Divvala.

[7] "Object Tracking for Surveillance Applications: A Comprehensive Review" by Mohamed Hussein, Hatem Rashwan, and Maha Sharkas.

[8] "Vision-Based Human Detection and Tracking for Incident Analysis in Intelligent Transportation Systems" by Jongmin Yu and Moongu Jeon.