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AI-Based Real-Time Animal Detection and Alert System for Nighttime Road Safety

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ABSTRACT: Unexpected animal crossings on the road are a serious risk, especially at night when visibility is poor. The suggested solution includes an intelligent animal identification and alert framework with the goal of improving road safety through ongoing monitoring in order to address this issue. The system makes use of a high-resolution night-vision camera to record traffic in real time, allowing for round-the-clock monitoring under difficult circumstances. Even in dim or hazy conditions, deep learning methods like You Only Look Once (YOLO) and Convolutional Neural Networks (CNN) are used to reliably identify animals. The device lowers the chance of collisions by instantly sending out alarm signals to warn oncoming cars upon detection. This automated method reduces human interaction and offers a scalable solution appropriate for rural and highway roads. The integration of AI-based vision technology with real-time detection ensures rapid response and efficient performance. The suggested solution seeks to greatly lower animal-related traffic accidents and increase nighttime driving safety by fusing automation, deep learning, and proactive alert systems.

KEYWORDS: Animal Detection, Highway Safety, Night-Vision Camera, Deep Learning, Convolutional Neural Networks (CNN), YOLO, Real-Time Alert System, Road Accident Prevention

I. INTRODUCTION

In contemporary transportation systems, road safety has grown in importance, especially in light of the growing number of animal-vehicle incidents. Both domestic and wild animals frequently wander into traffic lanes on rural and highway roads, resulting in serious collisions, human injuries, and animal deaths. These occurrences endanger ecological equilibrium in addition to causing financial losses and traffic jams. Because there is less visibility and slower reaction times for drivers at night, the risk of such collisions is particularly significant. Because they don't provide real-time awareness of animal movement, traditional safety measures like reflective boards, fences, and static warning signs are only partially successful. Intelligent surveillance and automated detection techniques are now crucial for improving road safety in order to address these issues. With an emphasis on nighttime, when accident rates are at their peak, this study suggests an advanced animal identification and alert system that continuously monitors road areas. In order to detect and identify animals approaching or crossing the road, the suggested system combines computer vision, deep learning, and real-time image processing. The system can reliably differentiate animals from other moving objects thanks to high-resolution night-vision cameras, environmental sensors, and clever algorithms. When an oncoming vehicle is detected, the system instantly produces visual and audio notifications, enabling drivers to react quickly and lowering the danger of an accident. Visual perception systems have been greatly enhanced by recent developments in artificial intelligence, especially deep learning. Even in low-light, foggy, or unfavorable weather, Convolutional Neural Networks (CNN) and the YOLO (You Only Look Once) architecture have shown remarkable accuracy in object detection tests. By utilizing these strategies, the suggested framework guarantees quicker and more accurate identification than conventional image processing techniques, making it appropriate for use on highways and isolated routes where manual monitoring is not feasible. The method supports more general societal and environmental goals in addition to its immediate safety benefits. In addition to saving lives, eliminating animal-vehicle collisions helps conserve wildlife by lowering needless animal deaths. The suggested system, which combines adaptive learning, ongoing monitoring, and real-time alarm mechanisms to offer a sustainable, cutting-edge solution for reducing nighttime traffic accidents brought on by animal crossings, is a major step toward smart road infrastructure. The performance of an object identification model applied to wildlife photos, where creatures like tigers, jaguars, and

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elephants are automatically recognized and located, as depicted in the figure 1. Bounding boxes are drawn around identified animals in each image, along with class labels and matching confidence scores that show how accurate the model's predictions were. A few red boxes show misclassifications or lower-confidence predictions, whereas green boxes emphasize the majority of detections, indicating proper classifications. The challenges presented by various locations, including forests, poor illumination, occlusion, and different animal positions, are reflected in the difference in confidence levels across distinct photos.

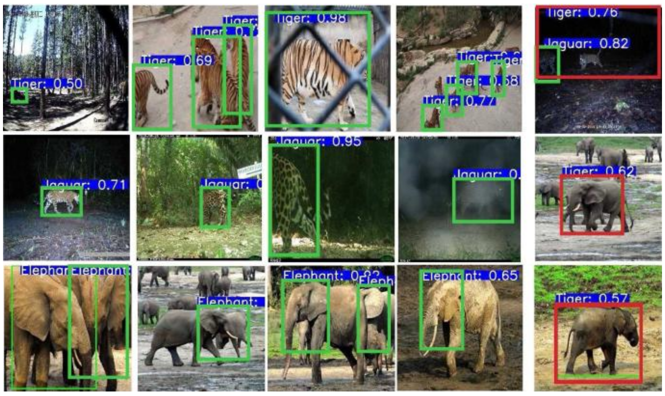

FIG 1: OBJECT DETECTION AND CLASSIFICATION

II. LITERATURE SURVEY

A thorough scoping overview of machine learning-based sensor data fusion methods for animal monitoring is presented by Aguilar-Lazcano et al. [1], emphasizing the recent developments and difficulties in this area. Accelerometers, GPS, acoustic, thermal, photo, and biometric sensors are just a few of the sensing modalities that are methodically examined in this paper. It also describes how various fusion strategies, such as raw-level, feature-level, and decision-level fusion, are used to merge data from these sources. The review highlights the complimentary nature of these sensors, with camera and auditory inputs contributing deep behavioral and identification insights and inertial and GPS data providing dependable geographical and temporal information. Additionally, it highlights common methodological trends, like the increasing usage of lightweight models appropriate for edge devices and the extensive use of supervised learning for classification tasks. The authors do, however, highlight several significant drawbacks, such as inconsistent data annotation, a lack of transparency regarding dataset biases, and a lack of benchmarking across diverse ecological contexts. In order to guarantee that these technologies can be successfully and morally implemented in actual animal monitoring systems, the research suggests creating standardized datasets, enhancing evaluation procedures, and fostering greater interdisciplinary cooperation.

An end-to-end deep learning framework for real-time animal behavior classification on resource-constrained embedded devices was proposed by Arablouei et al. [2]. In order to enable simultaneous feature extraction and classification from accelerometer data, the method presents a unique architecture that combines convolutional processes with recursive filtering techniques employing effective IIR and FIR filter layers. This concept is ideal for deployment on low-power edge devices like collar tags since it greatly decreases computational complexity while maintaining good accuracy. In comparison to conventional convolutional time-series models, experimental evaluation on real-world datasets shows high intra- and inter-dataset performance as well as significant improvements in important efficiency measures including inference delay, memory usage, and energy consumption. In order to guarantee dependable performance under hardware limitations, the study additionally emphasizes useful implementation techniques like pipeline optimization and quantization-aware training. The scientists do point out several drawbacks, including as sensitivity to sensor location and the requirement for more varied training datasets to capture changes among animal species, ages, and environmental circumstances. All things considered, the work offers a workable and efficient way to enable autonomous, real-time animal behavior monitoring in field settings.

In order to address the challenges of assessing social and group behaviors, Pereira et al. [3] presented SLEAP, a scalable deep learning system for multi-animal posture estimation and tracking. Both professionals and non-specialists can use the system's adaptable and modular pipeline, which supports a variety of model topologies, interactive annotation tools, and standardized data forms. It combines two complimentary techniques for body-part grouping and identification tracking, enabling precise pose estimate even in difficult situations involving close animal interactions

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and occlusion. SLEAP delivers great accuracy while preserving reproducibility and ease of use, as demonstrated by extensive benchmarking across several species and experimental circumstances. Important design elements that greatly reduce human labelinglabor and boost behavioral analysis efficiency include flexible network backbones, adaptable post-processing processes, and reliable identity tracking across time. Beyond its technical contributions, SLEAP is an open, well-documented platform that facilitates repeatable research in disciplines like neuroscience and ethology, allowing for the large-scale, automated extraction of intricate behavioral insights that were previously challenging and time-consuming to obtain.

A machine-learning approach that makes use of multidimensional data streams from automated monitoring and milking systems was proposed by Zhou et al. [4] to enable the early prediction of prevalent health issues in dairy cows. The method incorporates a variety of factors into supervised learning models, including milk yield, activity levels, rumination patterns, electrical conductivity, lactation stage, and seasonal influences. This enables the system to detect early indicators of conditions like metritis, lameness, and subclinical ketosis before clinical symptoms manifest. The study identifies the best algorithms for precise prediction through comparative analysis and highlights the significance of early diagnosis in lowering financial losses and enhancing animal welfare. Furthermore, interpretability techniques are employed to emphasize the most important characteristics for various health situations, offering insightful information for making decisions. The authors also discuss important issues, such as the difficulties of generalizing models across farms with different management techniques, synchronization of diverse sensor data, and class imbalance in datasets. In order to ensure dependability and scalability in real-world applications, the study emphasizes the need for external validation on separate datasets and recommends the practical integration of these prediction models into herd management systems.

A viewpoint on the revolutionary role of machine learning in animal conservation is presented by Tuia et al. [5], highlighting both its promise and the issues that need to be resolved for successful real-world impact. The authors point out that an explosion of ecological data has resulted from the quick development of inexpensive sensors and citizen-science projects. However, because of inconsistent data standards and the complexity of ecological systems, current processing techniques frequently fail to transform this raw data into insightful and useful conclusions. In order to get around these restrictions, the paper promotes hybrid approaches that combine ecological domain knowledge with machine learning techniques. This allows for the creation of interpretable and generalizable models for uses like behavioral studies, species distribution analysis, and population monitoring. Important practical approaches are also covered, such as using transfer learning to deal with a lack of labeled data, incorporating uncertainty quantification to improve conservation decision-making, and encouraging open data practices and repeatable workflows to improve cooperation between data scientists and ecologists. In order to ensure that advances in machine learning can be successfully turned into large-scale, quantifiable conservation benefits, the authors conclude by advocating for additional investment in transdisciplinary training and infrastructure.

A comprehensive assessment of the literature on the use of deep learning approaches for precise livestock recognition and localization utilizing unmanned aerial vehicles (UAVs) is presented by Yousefi, DB Mamehgol, et al. [6]. The study classifies several imaging modalities and sensing platforms, such as thermal, RGB, and multispectral sensors installed on UAVs, and examines how these technologies are incorporated into aerial surveillance systems. It also looks at annotation techniques, dataset preparation procedures, and important trade-offs such processing latency, flying altitude, and spatial resolution, all of which have a big impact on detection accuracy. The article contrasts various model designs, including lightweight convolutional networks, single-stage detectors, and two-stage detectors, emphasizing both their advantages and disadvantages in terms of generalization across various species and environments. The authors also address practical deployment issues, such as limitations imposed by regulations, short battery life, vegetation interference, and striking a balance between onboard and ground-based processing. The study suggests model compression for effective edge deployment, domain adaption strategies, and uniform benchmarking as solutions to these problems. It ends by pointing up significant research gaps, such as strengthening transferability across farming contexts, increasing robustness under different lighting conditions, and resolving ethical issues pertaining to possible animal distress during UAV operations.

The main obstacles preventing the successful use of machine learning in agricultural big data contexts are systematically analyzed by Cravero, Ania, et al. [7]. The study identifies important data-related problems that make it difficult to develop trustworthy machine learning models, such as the heterogeneity of data sources (such as satellite imagery, sensor networks, and farm management systems), inconsistent metadata standards, and the existence of missing or noisy labels. Beyond technological obstacles, the authors highlight socio-technical issues that prevent widespread adoption, such as worries about data ownership, a lack of platform compatibility, and a lack of technical

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know-how at the farm level. The study suggests that lightweight and explainable models are frequently more appropriate for real-world agricultural situations with limited resources by contrasting intricate, high-capacity models with simpler, easier-to-understand alternatives. It illustrates through case studies how biased or unrepresentative datasets can have a detrimental effect on model performance and suggests ways to improve generalization, including active learning, federated learning, and rigorous cross-site validation. Along with interdisciplinary cooperation, the authors support improved policy frameworks, shared infrastructure, and the development of high-quality public datasets. All things considered, the article provides useful advice for creating reliable, repeatable, and scalable machine learning workflows that are suited to the requirements of the agriculture sector.

An integrative framework for precision agriculture that integrates machine learning and Internet of Things (IoT) data analytics to improve farm management and decision-making was proposed by Akhter, Ravesa, Shabir Ahmad Sofi, et al. [8]. The framework offers a comprehensive architecture made up of dispersed sensor nodes that gather information on crop health, soil moisture, and microclimate variables. These nodes are backed by cloud-edge processing layers and a communication network. In order to extract valuable insights from diverse data streams, these layers employ both supervised and unsupervised learning approaches. For applications like irrigation scheduling, illness prediction, and yield estimation, the paper highlights important procedures including feature engineering, temporal synchronization of multimodal data, and predictive modeling. Additionally, it contrasts deployment options, emphasizing the trade-offs between more potent cloud-based analytics and low-latency, energy-efficient edge processing. Pilot projects in the real world show significant gains in crop stress detection and water efficiency. However, the authors point out issues include drift in sensor calibration, a lack of data in small-scale farms, and the requirement for model adaption that is specific to a certain area. The study suggests modular system architecture, ongoing model updating using real-time data, and the incorporation of domain expertise to improve interpretability and user confidence as solutions to these problems. All things considered, the study presents IoT-enabled machine learning as a workable and scalable way to achieve effective, data-driven agriculture when backed by solid system design and usability considerations.

By combining small unmanned aircraft systems (sUAS) with deep learning models tailored for aerial imagery processing, Zhou, Meilun, et al. [9] proposed a sophisticated method of animal monitoring. In order to improve resolution and detection accuracy, the work introduces preprocessing approaches such perspective correction and multi-frame image stitching to meet major obstacles in animal detection and localization from both oblique and nadir viewpoints at different elevations. Through contextual modeling that makes use of environmental signals and multi-scale feature fusion, the suggested deep convolutional networks are tuned to handle class imbalance and small-object recognition. Incorporating temporal consistency and motion information from consecutive frames greatly enhances detection ability, according to experimental results in a variety of ecosystems. Practical deployment factors, such as effective flight planning, reducing animal disturbance, and cooperation with ground-based monitoring teams, are also included in the study. It also looks at the trade-offs between computing demands and broad aerial coverage, suggesting hybrid processing approaches that combine high-resolution ground-based analysis with onboard filtering. In order to enable scalable and repeatable developments in this sector, the research highlights critical applications such animal population surveys, anti-poaching initiatives, and emergency monitoring. It also stresses the necessity of shared datasets and standardized methodologies.

An effective deep learning-based method for classifying animal behaviour that is especially tailored for embedded systems and edge deployment was presented by Arablouei, Reza, et al. [10]. In order to accurately identify animal behaviours using wearable sensor data, such as accelerometers and gyroscopes, the paper presents a compact model architecture that blends neural feature extraction with time-series modelling. The model uses a number of engineering improvements, such as temporal down sampling, parameter trimming, and quantization-aware training, which greatly reduce computing complexity while maintaining accuracy in order to satisfy the limitations of low-power devices. The suggested method is appropriate for battery-powered tracking devices since experimental evaluations show that it maintains low inference latency and energy consumption while achieving competitive classification performance. Additionally, the study offers comprehensive implementation insights that are useful for deployment on microcontrollers and low-power systems-on-a-chip. These insights include effective memory management, fixed-point arithmetic, and real-time scheduling algorithms. To guarantee consistent performance across various animals and habitats, the authors do admit several limitations, such as sensitivity to sensor placement and the requirement for calibration. All things considered, the work offers a workable and scalable method for ongoing, real-time animal behaviour monitoring in situations where energy efficiency is crucial and connectivity is restricted.

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III. EXISTING METHODOLOGIES

Road signs, speed breakers, and protective fences are examples of classic, passive solutions that only give drivers limited cautions without actively identifying possible hazards. These measures are mostly responsible for road safety in animal-crossing zones. Motion sensors and simple security cameras are used in some places to keep an eye on movement, but they are unable to correctly identify things, which makes it challenging to differentiate between vehicles, animals, and environmental disturbances. Furthermore, a lot of traditional setups rely on manual camera footage monitoring, which is laborious and prone to human mistake. Current automated methods mostly rely on basic motion detection and conventional image processing methods, which frequently lead to high false alarm rates because of things like passing cars, shadows, and moving vegetation. Additionally, these systems' alarm mechanisms are mostly reactive rather than proactive, which limits the amount of time drivers have to react and lowers their efficiency in preventing accidents. They also function poorly in low light and bad weather.In addition to these drawbacks, conventional road safety systems lack real-time intelligence and adaptability, which are essential in dynamic settings like rural roads and freeways where animal movement is erratic. Seasonal migration patterns, abrupt animal crossings, and time-specific hazards like greater animal activity at night or in the early morning cannot all be taken into account by static warning signs. Similar to this, fences and speed breakers might not be practical or effective in many types of terrain, particularly in open grazing regions or woodland corridors where animals can readily get around physical barriers. The lack of data-driven decision-making in traditional systems is another significant disadvantage. These methods limit the ability to apply preventive measures or improve road safety planning since they do not gather or examine previous data on animal movement patterns, accident hotspots, or traffic behaviour. Authorities are unable to precisely identify high-risk areas or implement focused actions without cognitive analytics. Furthermore, the efficacy of current methods is further diminished by their lack of connection with contemporary communication technologies. Smart traffic signals, mobile notifications, and in-car technology do not give drivers timely indications that may greatly enhance situational awareness and reaction time. Additionally, in the event of an animal-vehicle collision, emergency response systems are not automatically activated, which causes aid to be delayed. The efficacy of conventional monitoring systems is severely hampered by environmental elements including fog, rain, dust, and dim lighting, rendering them unreliable under dire circumstances. The necessity for strong and clever solutions is further highlighted by the fact that these conditions frequently correspond with increased accident risks. All things considered, the limitations of traditional systems underscore the pressing need for sophisticated, automated, and intelligent road safety solutions that are capable of precise real-time detection, categorization, and warning production. Artificial intelligence, computer vision, and sensor fusion are examples of technology that can be integrated with passive safety measures to create proactive systems that can greatly reduce animal-vehicle collisions and improve both wildlife conservation and human safety. And described in fig 2.

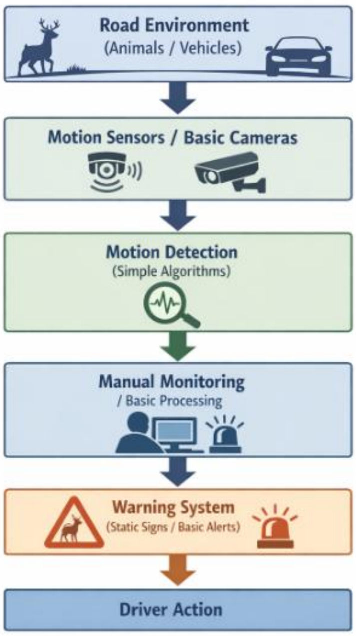

Fig 2: Existing block diagram

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IV. PROPOSED METHODOLOGIES

In order to prevent collisions, especially at night, the suggested system presents an automatic and intelligent framework that can identify the presence of animals on highways and promptly send out alerts. This study combines real-time image processing with cutting-edge deep learning methods to achieve excellent detection accuracy in a variety of environmental conditions. Roadways are equipped with high-resolution night-vision cameras to record live video and keep an eye on the environment. A Convolutional Neural Network (CNN) and YOLO-based detection model are used to process the recorded video frames and determine the existence, kind, and movement of animals in real time. The technology notifies drivers and lowers the chance of collisions by turning on instant warning features like flashing lights or aural notifications as soon as detection takes place. This study uses adaptive machine learning algorithms that can differentiate animals from other things, such cars, pedestrians, or ambient motion, in contrast to traditional systems that only rely on motion sensors or static detection thresholds. Large-scale image datasets gathered from public sources and real-world situations are used to train the deep learning model to identify various animal species and postures. Even under low-light, foggy, or wet conditions, the model can accurately identify complicated road conditions through feature extraction and region-based identification. The use of background removal and median filtering further improves image clarity and removes visual noise, guaranteeing reliable performance independent of changes in lighting or weather. The suggested approach prioritizes real-time reaction and system efficiency in addition to precise detection. The model uses the YOLO (You Only Look Once) architecture to quickly localize and classify objects in a single computational pass, enabling detection speeds appropriate for situations with fast-moving traffic. To give drivers instant visual or audio alerts, the alert module is linked with in-car displays or traffic control systems. Furthermore, the system's modular architecture facilitates scalability, allowing for deployment across rural roads, highways, and wildlife-prone locations. In order to improve nighttime road safety and reduce animal-vehicle incidents, this study presents a thorough and cutting-edge method that integrates deep learning, intelligent vision, and real-time warning. The suggested architecture diagram is shown in Figure 2.

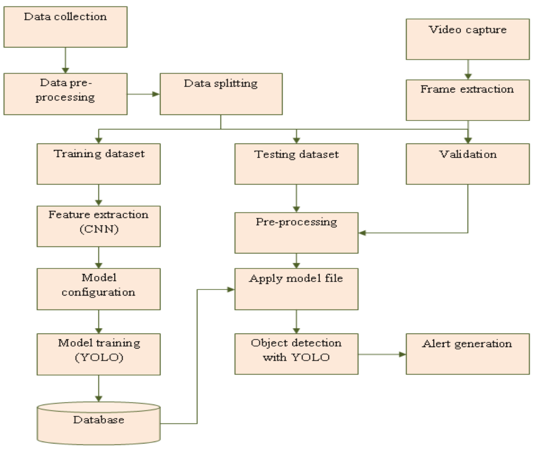

Figure 2: Architecture diagram of the proposed animal monitoring system.

V. METHODOLOGY

In order to accomplish precise and real-time animal recognition on roads, this research employs an organized and methodical pipeline that combines deep learning, image processing, and intelligent alarm systems. Initially, a variety of photos and videos of animals in different environments are collected utilizing cameras and publicly accessible databases. Preprocessing comes next. To improve quality and guarantee consistency for model training, the data is cleaned, resized, normalized, and enriched. Deep learning methods, specifically Convolutional Neural Networks (CNN), are used in the feature extraction stage to automatically identify and extract significant visual features from the input data.After processing, the data is sent to the object detection step, where the YOLOv11 model uses bounding boxes and confidence scores to locate and identify animals in real time. The identified objects are then classified into distinct categories, such as vehicles, animals, or other entities, using object recognition. Lastly, when an animal is found close to or on the road, an alert generation module is activated, giving drivers timely visual or audible warnings. Together, these phases provide a strong, effective, and intelligent system that improves nighttime road safety and lowers animal-vehicle collisions.

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Data Collection

The first stage entails compiling an extensive dataset of animal photos and videos from both proprietary road surveillance recordings and open-source repositories like Kaggle. The collection contains a variety of animal species, sizes, and poses that were photographed in different lighting and environmental settings. The model can successfully generalize and identify animals in actual traffic situations thanks to this varied dataset. To guarantee precise model evaluation and avoid overfitting, the dataset is split into training and testing subsets. In order to support supervised learning for object detection algorithms, bounding boxes are marked around animals in the gathered data.

Image Preprocessing

In order to improve image quality and get data ready for model training, preprocessing is an essential step. At this step, methods like median filtering are used to enhance clarity and eliminate noise, especially in low-light photos. To guarantee uniformity throughout the dataset, image scaling and normalization are carried out. The system can concentrate on foreground activity by separating moving items from static scenes using background subtraction and binarization techniques. By removing unnecessary information and improving the visibility of animal outlines, these preprocessing procedures greatly enhance the performance of later feature extraction and detection stages.

Feature Extraction

Feature extraction is the process of examining every image to find key visual elements including texture, color, and shape. Using several convolutional and pooling layers, the Convolutional Neural Network (CNN) architecture automatically retrieves hierarchical features. Through this approach, meaningful feature maps that depict the distinctive qualities of animals are created from raw pixel data. CNN-based extraction offers greater flexibility and resilience than conventional techniques that rely on human feature selection. In order to accurately distinguish between animals and non-animal things, the retrieved characteristics are used as the input for classification and detection algorithms.

Object Detection

The YOLO (You Only Look Once) method, which locates and classifies animals in video frames in real time, is used to detect objects. YOLO divides the image into grids and simultaneously predicts bounding boxes and class probabilities, processing the full image in a single pass. Because of its remarkable detecting speed and precision, its design is appropriate for dynamic road settings. Multiple animals can be identified by the model in a single frame, even if they are positioned at different distances or are only partially visible. Rapid reaction is ensured by YOLO's architecture, which is essential for timely alert production in situations with heavy traffic.

Object Recognition and Classification

After detection, object recognition is used to determine the kind of animal and more confidently establish its existence. Based on the attributes that were extracted, the CNN classifier identifies the creatures that were found. Differentiating between different species, such as deer, dogs, cattle, or other wildlife frequently seen on highways, is made possible by this recognition phase. The approach lowers false positives while retaining sensitivity to real detections because to the combination of CNN and YOLO, which improves precision and recall rates.

Alert Generation System

Real-time alert activation is the methodology's last step. When an animal is seen and confirmed, the system alerts drivers by activating warning features including sirens, flashing road lights, or dashboard alerts. Instantaneous and context-aware alerts are made to provide enough reaction time to prevent collisions. To improve situational awareness, the alert module can be linked with current vehicle communication systems or traffic control infrastructure. This automated procedure greatly increases nighttime road safety by ensuring that authorities and drivers are instantly advised of potential threats.

VI. EXPERIMENTAL RESULTS

The accuracy, processing speed, and real-time performance of the suggested animal identification and alert framework for road safety were evaluated experimentally. The experimental dataset was assembled from real-world nighttime road surveillance media and open-source repositories. Deep learning models including YOLOv11, Faster R-CNN, and Single Shot Detector (SSD) were used to examine the system's performance. To provide a fair comparison, every model was trained and tested on the same dataset under the same circumstances. Frame processing speed (FPS), detection accuracy, and system robustness in low light were among the evaluation measures. The findings show that in terms of detection accuracy, speed, and flexibility, the YOLOv11 model outperformed the other models. The suggested framework proved to be highly effective in detecting animals in a variety of lighting and weather scenarios. During

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real-time video analysis, the system consistently performed and successfully decreased false detections. The framework achieved the best possible balance between computing efficiency and detection accuracy by utilizing CNN-based feature extraction and YOLO's one-stage detection technique. This makes it perfect for deployment in dynamic traffic settings. The assessment also showed that, although accurate, Faster R-CNN had slower inference speeds, which made it less appropriate for real-time detection. Although SSD produced mediocre results, it had trouble identifying small or partially visible creatures in low light. The following table provides a summary of these models' overall comparison:

Model	Accuracy (%)	Processing Speed (FPS)	Strengths	Weaknesses
YOLOv11	92.5	30–60	High speed, strong accuracy, real-time capable	May require retraining for rare animal types
Faster R-CNN	89.2	5–10	High precision, stable detection	Slow inference, unsuitable for fast traffic scenes
SSD (Single Shot Detector)	85.4	20–30	Balanced speed and accuracy	Limited performance on small or distant objects

Table 1: Performance Comparison of Detection Models

The findings unequivocally show that YOLOv11 is the best algorithm for real-time road monitoring applications since it performs faster and more accurately than the other models. With constant frame processing of up to 60 frames per second, the model produced an average detection accuracy of 92.5%, allowing for quick warning production and low latency. This guarantees efficient functioning in situations where prompt driver alerts and system reactions are necessary.

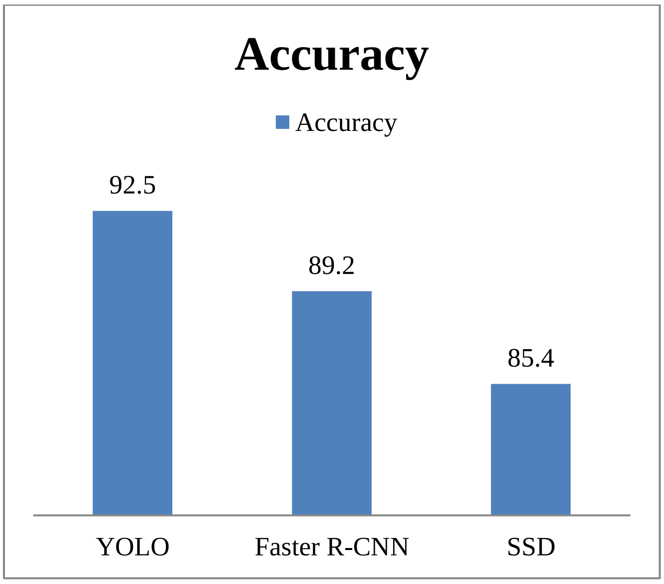

Figure 3: Accuracy chart

The total testing result confirms the effectiveness of the suggested technique in obtaining very accurate real-time animal detection. Even in high-speed and low-light conditions, consistent functionality is made possible by the integration of deep learning and improved image processing techniques. The findings verify that this study offers a workable and expandable way to enhance traffic safety and reduce animal-vehicle incidents, especially at night.

V. CONCLUSION

For the purpose to enhance road safety, especially at night, this study suggests a thorough and sophisticated framework for animal recognition and alarm generating. The system successfully identifies animals coming or crossing roads by combining computer vision, deep learning, and real-time processing. It then promptly issues alert to assist avoid collisions. It is appropriate for dynamic traffic scenarios because it uses Convolutional Neural Networks (CNN) in

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conjunction with the YOLOv11 architecture to provide precise detection and classification with low latency. According to experimental data, YOLOv11 is more accurate and faster than conventional models like SSD and Faster R-CNN, demonstrating its usefulness for real-time applications.The system's robustness for practical deployment is further demonstrated by its great performance in low light and unfavorable weather. By lowering animal-vehicle collisions, the suggested strategy not only increases road safety but also supports wildlife conservation. Intelligent road infrastructure is based on the combination of adaptive alarm mechanisms and automated vision-based monitoring. Multi-sensor fusion, thermal imaging, and cloud-based alert systems are examples of future improvements that could increase detection precision and operational effectiveness. All things considered, this work demonstrates how artificial intelligence may facilitate proactive monitoring and decision-making for safer and more intelligent transportation systems.

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