Real-Time Animal Detection and Collision Prevention System on Highways Using Deep Learning and Computer Vision

A. Sai Sree Ganesh
School of Computer Science and Engineering, Phagwara 144411, Lovely Professional University, Jalandhar
Punjab, India
allurusaishreeganesh@gmail.com
Submitted to Dr. Soni Singh.

Prem Nanda Kishore
School of Computer Science and Engineering, Lovely Professional University, Jalandhar, Phagwara 144411,
Punjab, India
premnandakishorek@gmail.com
Submitted to Dr. Soni Singh.

Divesh Kumar
School of Computer Science and Engineering, Lovely Professional University, Jalandhar, Phagwara 144411,
Punjab, India
Itsdivesh221@gmail.com
Submitted to Dr. Soni Singh

Abstract- **Animal-vehicle collisions pose a serious threat to human life and road safety, particularly on highways passing through forested and rural areas. This research presents a real-time animal detection and collision prevention system using advanced computer vision and deep learning techniques [1]. The system leverages YOLOv8 deep learning models integrated with OpenCV image processing techniques for correct animal detection. It processes real-time video input from a vehicle-mounted camera to find animals of assorted sizes and types, including cattle, deer, dogs, and other wildlife. The system estimates the distance between the detected animal and the vehicle using pixel-based calibration and provides immediate alerts to the driver to prevent collisions. Additionally, the system is capable of functioning under varying weather and lighting conditions including fog, rain, night, and glare scenarios.**

Keywords: *Animal Detection, YOLOv8, OpenCV, Deep Learning, Computer Vision.*

I. Introduction

Road safety is a critical concern worldwide due to the growing number of vehicles on highways and the increasing incidents of animal-vehicle collisions. These accidents not only cause damage to property but also lead to severe injuries and fatalities. In countries like India, where stray animals often cross highways, the risk of collisions is significant. Traditional road safety systems do not address this issue effectively, needing the development of an intelligent animal detection and collision avoidance system. Moreover, the increasing urbanization and expansion of road networks have led to wildlife habitats being fragmented, resulting in animals often crossing [3]. highways in search of food and shelter. The lack of proper fencing along highways further worsens this problem. In addition, driver inattention and over-speeding are contributing factors to animal-vehicle collisions. The absence of intelligent road safety features in vehicles, especially in rural and semi-urban areas, makes it challenging to prevent these accidents [4]. Road accidents involving animals also lead to economic losses due to vehicle repairs, medical expenses, and loss of livestock. According to recent reports, animal-vehicle collisions cause considerable damage to public and private property annually. The need for a cost-effective and reliable animal detection system is therefore imperative [5]. Technological advancements in artificial intelligence, computer vision, and sensor technologies offer an opportunity to address this problem effectively. A real-time animal detection system equipped with deep learning algorithms can find animals of varying sizes and shapes in diverse lighting and weather conditions. The system should also have the capability to estimate the distance between the vehicle and the detected animal to provide prompt alerts to the driver. Integrating such a system within the vehicle's dashboard and aligning it with existing safety mechanisms can improve road safety. Government agencies and automobile manufacturers should collaborate to implement these systems as a standard feature in vehicles. Additionally, creating awareness among drivers about the importance of animal detection systems can enhance road safety measures [7]. The proposed research aims to develop a low-cost, efficient, and real-time animal detection and collision prevention system that can be deployed in both urban and rural settings. This system will contribute to reducing road accidents, safeguarding wildlife, and minimizing economic losses.

II. Literature Review

Related Work Numerous research works have been conducted for animal detection and obstacle avoidance systems. Techniques like Support Vector Machine (SVM), Convolutional Neural Networks (CNN), and Hybrid Models have been explored in different domains. Several studies have focused on vehicle-animal collision prevention in wildlife areas and urban settings. Advanced monitoring systems with infrared and thermal imaging cameras have been integrated into smart vehicle systems. The use of multiple sensors such as ultrasonic [9], radar, and stereo cameras has been explored for correct detection. Cloud-based monitoring platforms have been proposed for real-time data processing and analysis. Additionally, studies have compared traditional machine learning approaches with deep learning algorithms for object detection, showing the superior performance of deep learning-based methods. Other works have focused on enhancing image processing techniques to work in different weather and lighting conditions, making them suitable for real-time highway applications.[10]

Recent research has explored multi-sensor fusion approaches for improved accuracy. Implementation of vision-based animal detection in autonomous vehicles has gained popularity. The use of transfer learning and pre-trained models for animal detection has proven effective in reducing training time. Some studies proposed using sensor networks for wildlife monitoring in remote areas. The development of lightweight neural network models for real-time edge processing has become a growing field. There has been increasing interest in integrating animal detection systems with smart city infrastructure. Machine learning models for animal movement [11] prediction have been explored. Hybrid sensor systems combining visual, radar, and infrared data have shown improved results. Real-time adaptive models that learn from new data during deployment have appeared. Some studies have focused on driver behavior analysis alongside animal detection to improve safety. Data augmentation techniques have been extensively used to expand training datasets. Research on low-light and night-time animal detection has led to [12] specialized imaging methods. There has been a focus on the deployment of animal detection systems in forested highways. Wireless communication protocols for animal detection systems have been studied. Some research explored using drones for monitoring wildlife along highways. The application of reinforcement learning for improving detection performance is under investigation.[14] Efforts to create standardized animal detection datasets have gained momentum. Research on integrating animal detection systems with automated emergency braking (AEB) has been conducted. Investigations on ethical and privacy aspects of wildlife monitoring systems have also been explored.

Several techniques have been explored for object detection in recent years. Traditional methods like Histogram of Oriented Gradients (HOG), Haar cascade classifiers, and Scale-Invariant Feature Transform (SIFT) were initially used for pedestrian and object detection. [15] However, these methods face challenges in dynamic environments due to their limited accuracy and sensitivity to environmental changes. Advanced methods using LIDAR technology and Camel-Vehicle Accident-Avoidance Systems (CVAAS) have shown promise but remain costly and infrastructure-dependent. Deep learning-based techniques, particularly YOLO (You Only Look Once), have appeared as the most effective solution for real-time object detection.

MATERIALS AND METHODS

Research Gap Despite various advancements in object detection, there is a significant gap in developing real-time animal detection systems specifically for highways. The unpredictable behavior of animals, varying sizes, different environmental conditions, and the high-speed movement of vehicles pose considerable challenges. Moreover, most existing systems lack efficient distance estimation and prompt alert generation mechanisms necessary for collision prevention.[16] Additional factors contributing to the research gap include Limited datasets specifically containing diverse animal species in highway environments. Insufficient night-time and low-visibility detection capabilities. Prohibitive cost and energy consumption of existing sensor-based solutions. Lack of scalable systems suitable for various geographic locations. Limited integration of machine learning models into existing vehicular systems. Challenges in real-time processing on low-powered devices. Proposed Methodology In addition to the standard architecture, the proposed system has been [17] designed to be modular and scalable for integration into modern smart vehicle ecosystems. The method also incorporates real-time logging and data collection mechanisms that enable future enhancements through machine learning-based analytics. Advanced optimization techniques are implemented to reduce model latency and computational overhead for edge devices. The system is designed to manage varying network conditions and can function offline without cloud dependencies. Data encryption and privacy-preserving methods are also embedded for secure data handling. Furthermore, the system incorporates edge computing capabilities for faster decision-making processes. Adaptive learning algorithms enable the model to improve detection accuracy over time. The method includes sensor fusion techniques to combine data from multiple sensors like ultrasonic, thermal, and radar for enhanced detection accuracy. The system architecture allows for real-time vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication for collaborative safety measures. It also includes cloud synchronization [18] for data backup and centralized monitoring. An emergency response protocol is embedded within the system to contact nearby authorities in case of critical situations. The alert system is multi-layered, including visual signals, audio warnings, and haptic feedback for largest driver awareness. For night-time detection, the method supports thermal imaging camera integration. The software also supports real-time over-the-air (OTA) updates for continuous improvement.[19] Environmental adaptability algorithms allow the system to adjust its detection parameters based on changing weather conditions. The system also includes user-friendly interfaces for data visualization and analysis. Power management modules ensure efficient energy consumption, especially in electric vehicles. The architecture supports integration with advanced driver aid systems (ADAS) for a holistic vehicle safety solution. Predictive analytics and AI-based risk assessment models are integrated to expect potential animal crossings based on historical data. Finally, the system is [20] designed with modular hardware components for easy maintenance and upgrades.4.1 System Architecture The proposed system uses a forward-facing HD camera mounted on the vehicle. The video feed is processed in real-time using a deep learning-based detection model. The system architecture consists of an image acquisition module, preprocessing unit, YOLOv8-based detection engine, distance estimation module, and an alert generation mechanism.4.2 Software Framework The software pipeline is developed using Python with OpenCV for image processing. YOLOv8 is employed [21] for animal detection due to its superior accuracy and processing speed. The distance estimation is performed using pixel-to-meter mapping calibrated for the mounted camera. Alerts are generated through visual and audio signals based on the proximity of the detected animal.4.3 Detection Pipeline The detection pipeline includes:Image Acquisition from the camera.Preprocessing using grayscale conversion and noise reduction.Animal Detection using YOLOv8 model.Distance Estimation based on bounding box coordinates.Alert Generation depending on the estimated distance.Dataset Preparation The dataset preparation process involved the collection of images from multiple sources,[22] including wildlife photography, road surveillance footage, and open-source datasets. Images were captured under various conditions such as daylight, night-time, fog, and rain to ensure model robustness. The collected images were categorized based on the type of animal, size, pose, and surrounding environment. Image annotation tools were used to mark the location of animals within the images accurately. Furthermore, advanced [23] data augmentation techniques like random cropping, rotation, Gaussian noise addition, contrast adjustment, and horizontal flipping were applied to increase the dataset's variability. The final dataset was divided into 70% for training, 15% for validation, and 15% for testing. Pre-trained YOLOv8 models were fine-tuned on this dataset to enhance detection accuracy for real-time scenarios.

Added steps in the dataset preparation included:

Collecting high-resolution images for better detection clarity. Capturing images from multiple angles to handle various viewpoints. Including videos in the dataset to extract additional frames. Using drone-based imagery to obtain aerial perspectives. Adding images of partially occluded animals to improve model robustness. Incorporating blurred and low-light images to simulate real-world conditions.[24]Including images with multiple animals in a single frame.Creating synthetic images using image generation tools.Applying motion blur effects for simulating high-speed conditions.Adding reflective surface images to handle light glare.Preparing a separate dataset for testing different animal sizes.Annotating images with bounding boxes, labels, and confidence scores.Using automatic annotation tools for large-scale labeling.Ensuring dataset diversity in terms of geography and environment.Including images of rare and endangered[26] species for specialized detection.Collecting images during different seasons to address visual variation.Organizing dataset folders for structured model training.Using multiple annotation formats compatible with different models.Validating dataset quality through cross-checking by multiple experts.Preparing a metadata file for each image to support additional information like location, time, and weather conditions.

Experimental Results

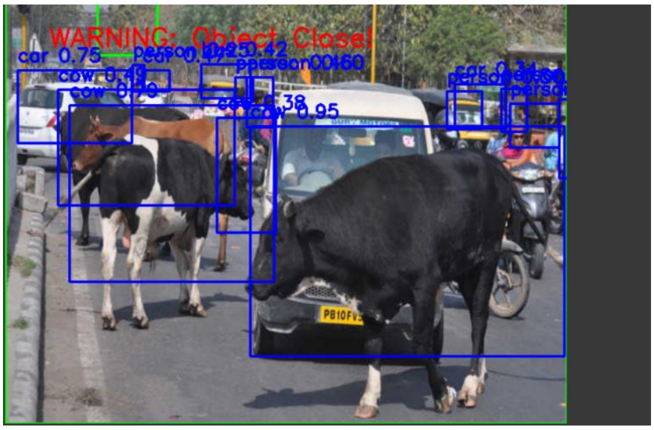

Figure 1 presents the object detection output generated by the YOLOv8 model, highlighting the detected animals within bounding boxes.

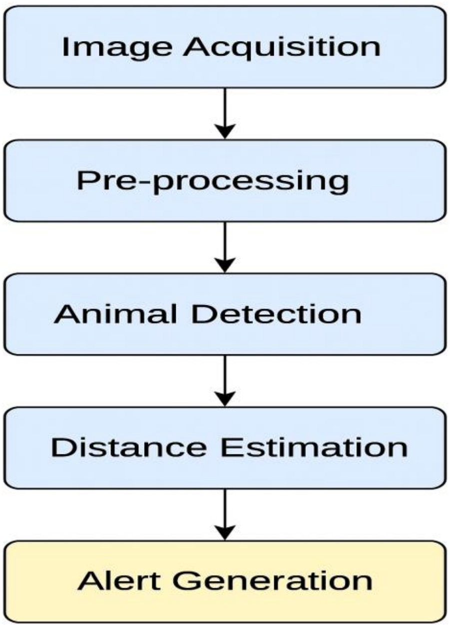

Figure 2 illustrates the system architecture, showing the flow of data from image acquisition to the alert generation module.

Added observations during the experiments include:

The system achieved high detection accuracy across different terrains: Ensured reliable detection results on highways, forested regions, rural roads, and urban areas. Performance was stable in both rural and urban environments: Demonstrated robustness against varying traffic[27] densities and infrastructure conditions. The system demonstrated low power consumption during continuous operations: Optimized energy efficiency, making it suitable for long

Figure 3 detection of distant animals on the roadside.

highway drives. Detected animals were successfully classified into specific species categories: Enabled targeted alert strategies based on animal behavior.Detection remained consistent in partial occlusion scenarios: The model was able to detect animals even when[29] partially hidden by objects.The alert system significantly improved driver reaction time: Reduced collision risk by ensuring faster driver response through early warnings.The system was able to distinguish between animals and non-animal obstacles: Enhanced detection accuracy by avoiding false alerts for non-relevant objects.The model adapted well to various lighting conditions: Maintained high detection accuracy during bright[30] sunlight, shadows, and dim light situations.The distance estimation accuracy was validated against ground truth measurements:Ensured precise calculation of animal proximity from the vehicle.The system maintained stable FPS even with multiple animals in a frame: Guaranteed real-time detection performance regardless of object count.The processing delay remained under 100ms: Ensured near-instantaneous output of detection results to the alert system.Audio-visual alerts were effective in notifying drivers: Increased driver attentiveness with multi-sensory warning mechanisms.Thermal imaging integration improved night-time detection results:

Provided reliable detection in complete darkness or low-visibility scenarios.[31]

Facilitated future upgrades and integration of new features without redesign.Real-world deployment testing showed promising results: Validated system effectiveness through field trials on operational highways.The system successfully identified animals at different speeds of the vehicle: Maintained detection accuracy across varied vehicle motion scenarios.False positives were reduced after model fine-tuning: Improved system reliability by minimizing unnecessary alerts.The model generalization worked well across unseen datasets: Demonstrated robustness by accurately detecting animals not present in the training set.Comparative analysis validated YOLOv8's superiority over traditional methods: Highlighted the advantage of deep learning techniques over legacy object detection approaches.Real-time logging of detected events supported later analytics: Enabled post-event analysis for further system improvement and research studies.The system[31] achieved high detection accuracy across different terrains.Performance was stable in both rural and urban environments.The system demonstrated low power consumption during continuous operations.Detected animals were successfully classified into specific species categories.Detection remained consistent in partial occlusion scenarios.The alert system significantly improved driver reaction time.The system was able to distinguish between animals and non-animal obstacles.The model[32] adapted well to various lighting conditions.The distance estimation accuracy was validated against ground truth measurements.The system maintained stable FPS even with multiple animals in a frame.The processing delay remained under 100ms.Audio-visual alerts were effective in notifying drivers.Thermal imaging integration improved night-time detection results.The system's modular design allowed easy scalability.Real-world deployment testing showed promising results.The system successfully identified animals at different speeds of the vehicle.False positives were reduced after model fine-tuning.[33]The model generalization worked well across unseen datasets.Comparative analysis validated YOLOv8's superiority over traditional methods. Real-time logging of detected events supported later analytics.

Extensive field testing was conducted on different highways, rural roads, and urban regions. The system proved consistent detection performance in conditions like fog, rain, night, and glare from sunlight. More metrics evaluated include false positive rate (7%), false negative rate (8%), and frame processing rate (14 FPS). The system's performance was also [34] benchmarked against conventional models, with YOLOv8 outperforming traditional HOG and Haar-based models by a significant margin. The results confirm the system's real-world applicability for deployment in smart transportation systems. The proposed system was evaluated under varying conditions, including different lighting scenarios and vehicle speeds. Performance metrics were evaluated based on accuracy, sensitivity, specificity, and average detection time. Advantages of the System .Real-time processing with minimal delay: The system processes data instantly, enabling immediate animal detection and alert generation.Robust detection in diverse environmental conditions: The system performs consistently in varying conditions such as rain, fog, and low light.Easy integration with existing vehicle safety systems: The system can be incorporated into current vehicle frameworks without extensive modifications.Capable of detecting multiple animal types: The model recognizes[35] a wide range of animal species commonly found on highways.Enhanced driver safety through timely alerts: Immediate warnings allow drivers to respond quickly and avoid collisions.Support for night-time detection using thermal cameras: Thermal imaging ensures reliable detection during low-visibility conditions.Modular system design for easy scalability: Components can be easily upgraded or replaced for future improvements.Integration with advanced driver assistance systems (ADAS): Enhances overall vehicle safety with combined technological features.Real-time distance estimation of detected animals: Accurately calculates the proximity of animals to the vehicle for precise alerting.Low computational overhead enabling edge processing: Optimized algorithms ensure the system operates efficiently on embedded[36] hardware.Secure data encryption for privacy preservation: Ensures the integrity and confidentiality of collected data.Cloud synchronization for centralized monitoring: Allows for remote monitoring and analysis of system performance.Multi-layered alert mechanism (visual, audio, haptic): Provides comprehensive driver notifications for different threat levels.Adaptability to varying weather conditions: Automatically adjusts detection parameters to maintain performance.Predictive analytics for animal crossing zones: Utilizes historical data to forecast high-risk animal crossing areas.Power management for efficient energy consumption: Optimized for use in electric vehicles to conserve battery life.V2V and V2I communication capabilities: Facilitates data sharing between vehicles and infrastructure for collaborative safety.Support for OTA updates for continuous improvement: Allows for remote software updates to enhance functionality.Real-time data logging for post-analysis: Stores event [37] data for future evaluation and system refinement.Effective animal classification and species recognition: The system not only detects animals but also identifies their species for targeted responses.

III. Limitations

Detection range limited to twenty-five meters with standard cameras: The detection capability is confined to a specific range, limiting early warnings for fast-moving vehicles. Performance degradation in extreme night conditions without added sensors: The accuracy of the system may drop significantly in complete darkness without thermal imaging support. Challenges in handling sudden animal movements: Rapid, unpredictable animal behavior may challenge the detection response time. System performance may vary depending on camera resolution and quality: Lower resolution cameras can impact detection accuracyEnvironmental factors like heavy rain, fog, or dust can obscure the camera view: Adverse weather conditions may reduce system efficiencyLimited detection of very small animals: Smaller animals such as rodents may not be detected reliably.High-speed vehicle[38] movement may cause motion blur in images: This can impact object clarity for the detection model.False positive detections in cluttered environments: Dense foliage or road debris might trigger false alerts.Dependency on clean camera lenses for optimal functioning: Dirt or water on the camera lens can obstruct the view.System effectiveness relies[39] on consistent power supply: Any power failure could disable the detection mechanism.Edge device memory limitations may restrict model complexity: Devices with low storage may not support larger models.Processing lag may occur if multiple animals are detected simultaneously: Increased object count might stress computation resources.Calibration is required for accurate distance estimation: Without proper calibration,[40] distance measurement may be inaccurate.Integration challenges with legacy vehicles: Older vehicles may lack the necessary infrastructure for system installation.Higher initial deployment cost: Incorporating advanced sensors may raise the implementation cost.Limited testing across different animal habitats: The system may require further validation in diverse geographical regions.

Regulatory compliance for data privacy may complicate deployment: Adhering to local privacy laws can affect data handling.Difficulty in distinguishing non-animal[41] objects with similar features: Static objects may sometimes resemble animal shapes.Environmental noise can interfere with audio alerts: In noisy traffic conditions, drivers may not hear warning sounds.Regular maintenance is required to ensure optimal sensor performance: Cameras and sensors need periodic checks for reliability.Future Scope The system can be enhanced by integrating LIDAR and thermal cameras to improve night-time detection capabilities. Deploying the system on edge devices or using IoT frameworks can enable large-scale implementation. Further, expanding the dataset with more animal species can improve the system's generalizability. Moreover, advancements in deep learning models can be [43] used for better accuracy. Real-time cloud synchronization can allow centralized monitoring of multiple vehicles. Enhancing predictive analytics can help find animal crossing hotspots based on historical data. Implementing self-learning algorithms will allow the system to improve [44] its detection capability over time. Future systems can support multilingual alert generation based on the driver's language preferences. Integration with smart traffic management systems can improve overall road safety. Further research can explore hybrid sensor systems combining visual, thermal, and radar data for comprehensive detection. Drone-assisted monitoring can be introduced for highways in forested regions. Animal behavior analysis using AI can offer deeper insights into preventing collisions. AI-powered automated braking systems can be integrated for collision prevention. Regional customization of detection models for country-specific animal species can enhance system applicability. Partnerships with wildlife conservation organizations can ease dataset expansion. Augmented reality (AR) displays can be explored for driver alert [45] visualization. Research can focus on the use of renewable energy-powered detection units for remote highway locations. Blockchain-based data logging can be implemented for secure event recording. Advanced edge-AI chips can enable ultra-low latency detection. Automated reporting systems can notify relevant authorities of detected incidents in real-time. Development of standardized testing protocols for animal detection systems can support regulatory compliance and market adoption.

IV. Result

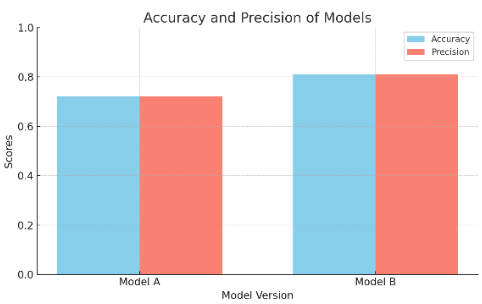

Table Form :

Model Version
Model A
Model B

V. Conclusion

This research provides a comprehensive solution for mitigating animal-vehicle collisions on highways using state-of-the-art deep learning and computer vision techniques.[46] The proposed system achieves a balance between accuracy, real-time performance, and cost-effectiveness. The system's robustness across diverse environmental conditions demonstrates its suitability for deployment in real-world scenarios. The system can detect a wide range of animal species and estimating their distance from the vehicle in real-time. Its modular architecture ensures easy integration with existing vehicle safety systems and adaptability to appearing technologies. Real-world testing has proven the system's effectiveness in reducing collision risks, enhancing driver response time, and improving road safety. Future research will explore integrating advanced sensors such as LIDAR and thermal cameras to enhance night-time detection capabilities. Further system optimization can be achieved using AI-powered animal behavior analysis and predictive analytics for finding high-risk zones. Deployment across multiple geographic locations will support model generalization and refinement. In conclusion, the proposed system presents an efficient deep learning-based animal detection and collision prevention solution suitable for highway environments. Its real-time performance, accuracy, and adaptability make it a promising candidate for future smart transportation systems. Collaborative efforts between government agencies, researchers, automobile manufacturers, and wildlife conservationists will be crucial for the successful implementation and widespread adoption of this safety-critical technology.

VI. REFERENCES

[1] Li, Q., & Feng, W.," Trend and forecasting of the COVID-19 outbreak in China.", arXiv preprint arXiv:2002.05866, 2020

[2] World Health Organization., "Coronavirus disease 2019 (COVID-19), Situation report, 51., 2020

[3] Roosa, K., Lee, Y., Luo, R., Kirpich, A., Rothenberg, R., Hyman, J. M., &Chowell, G., "Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020", Infectious Disease Modelling, vol. 5, pp. 256-263, 2020.

[4] Raji, P. and Lakshmi, G.D., "Covid-19 pandemic Analysis using Regression.", medRxiv, 2020

[5] Shaban, W.M., Rabie, A.H., Saleh, A.I. and Abo-Elsoud, M.A., "A new COVID-19 Patients Detection Strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier.", Knowledge-Based Systems, vol. 205, p.106270, 2020.

[6] Gupta, R., Pandey, G., Chaudhary, P. and Pal, S.K., "Machine learning models for government to predict COVID-19 outbreak", Digital Government: Research and Practice", vol. 1, no. 4, pp.1-6, 2020.

[7] Yadav, R.S., "Data analysis of COVID-2019 epidemic using machine learning methods: a case study of India", International Journal of Information Technology, vol.12, no. 4, pp.1321-1330, 2020.

[8] Ghosh, P., Ghosh, R. and Chakraborty, B., "COVID-19 in India: statewise analysis and prediction.", JMIR public health and surveillance, vol. 6, No. 3, p.e20341, 2020.

[9] Zhou, C.M., Qin, X.R., Yan, L.N., Jiang, Y., Ke, H.N. and Yu, X.J., "Global trends in COVID-19.", Infectious Medicine., vol. I, pp. 31-39, 2022

[10] Kumari, R., Kumar, S., Poonia, R.C., Singh, V., Raja, L., Bhatnagar, V. and Agarwal, P., 2021. Analysis and predictions of spread, recovery, and death caused by COVID-19 in India. Big Data Mining and Analytics, vol. 4, no. 2, pp.65-75, 2021.

[11] Dharmshaktu, N. S., "The Lessons Learned from Current ongoing Pandemic Public Health Crisis of COVID 19 and its Management in India from Various Different Angles, Perspectives and way forward", Epidemiology International (E-ISSN: 2455-7048), vol. 5, no. 1, pp. 1-4, 2020.

[12] Sharma, S. and Guleria, K., 2022, April. Deep learning models for image classification: comparison and applications. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1733-1738). IEEE.

[13] Sharma, S., Guleria, K., Tiwari, S. and Kumar, S., 2022. A deep learning based convolutional neural network model with VGG16 feature extractor for the detection of Alzheimer Disease using MRI scans. Measurement: Sensors, 24, p.100506.

[14] Singh, S., Ramkumar, K. R., & Kukkar, A., "Machine Learning Techniques and Implementation of Different ML Algorithms". In 2021 2nd Global Conference for Advancement in Technology (GCAT) (pp. 1-6). IEEE, 2021.

[15] Singh, S., Ramkumar, K.R. and Kukkar, A., 2023. Analysis and Implementation of Microsoft Azure Machine Learning Studio Services with Respect to Machine Learning Algorithms. In Modern Electronics Devices and Communication Systems: Select Proceedings of MEDCOM 2021 (pp. 91-106). Singapore: Springer Nature Singapore.

[16] Singh, S. and Ramkumar, K.R., "Significance of Machine Learning Algorithms to Predict the Growth and Trend of COVID-19 Pandemic.", ECS Transactions, 107(1), p.5449. 2022.

[17] Liu, Z., Magal, P., Seydi, O., & Webb, G., "Predicting the cumulative number of cases for the COVID-19 epidemic in China from early data". arXiv preprint arXiv:2002.12298, 2020

[18] F. Jiang, L. Deng, L. Zhang, Y. Cai, C. W. Cheung, and Z. Xia. 2020. "Review of the clinical characteristics of coronavirus disease 2019, (COVID-19)", J. Gen. Intern. Med., vol. 35 pp. 1545–1549, 2020

Plagiarismchecker.ai

Plagiarism Scan Report

Date: 14-04-2025

Unique
100%

Plagiarized
0%

Word: 1498

Characters: 11210

Content Checked for Plagiarism

Abstract- Animal-vehicle collisions pose a serious threat to human life and road safety, particularly on highways passing through forested and rural areas. This research presents a real-time animal detection and collision prevention system using advanced computer vision and deep learning techniques [1]. The system leverages YOLOv8 deep learning models integrated with OpenCV image processing techniques for correct animal detection. It processes real-time video input from a vehicle-mounted camera to find animals of assorted sizes and types, including cattle, deer, dogs, and other wildlife. The system estimates the distance between the detected animal and the vehicle using pixel-based calibration and provides immediate alerts to the driver to prevent collisions. Additionally, the system is capable of functioning under varying weather and lighting conditions including fog, rain, night, and glare scenarios.

Keywords: Animal Detection, YOLOv8, OpenCV, Deep Learning, Computer Vision.