JOURNAL OF DATA SCIENCE | Vol.2025, Issue 1, No.11
eISSN:2805-5160

Automatic Detection of Damaged Roads and Lane Detection using Deep Learning

Kotakonda. Sandhya Rani[1*], Kommi. Chandana[2], Nallamalla. Kavya[3], Kasireddy. Poojitha[4],Thalla. Pallavi[5]

[1,2,3,4,5] Vignan's Institute of Management and Technology for Women (VUMTW), India

Email: sandhya@vmtw.in[1*], chandana.kommi50@gmail.com[2], nallamallakavya@gmail.com[3], kasireddypoojitha26@gmail.com[4], pallavireddy.thalla@gmail.com[5]

Abstract

This project introduces an automated system for detecting road surface damages and identifying lane markings using Deep Learning, YOLO (You Only Look Once), and Canny edge detection. The main goal is to improve road safety, assist autonomous navigation, and support efficient infrastructure maintenance. Road damages, such as potholes and cracks, are detected in real-time from images or videos captured by cameras mounted on vehicles or drones. The YOLO algorithm is used to classify and localize these damages with high speed and accuracy. At the same time, the Canny edge detection method identifies lane boundaries, ensuring precise lane detection even in challenging environments. Combining these techniques results in a reliable and scalable solution for smart transportation systems. The system reduces the need for manual road inspection and enables authorities to prioritize repairs based on real-time information. It also supports safer navigation for autonomous and assisted vehicles.

Keywords

Automatic Road Damage Detection, Canny Edge Detection, Road Safety Enhancement, YOLO Algorithm

Introduction

Uneven roads with cracks and potholes may upset passengers, damage vehicles, and result in accidents. The rise of autonomous vehicles means it has become necessary to spot these obstacles. Deep learning-based methods are used by our project to tackle this issue. Our solution identifies potholes, stops them from being created by offering suggestions to authorities, and prevents drivers from accidents by giving prior pothole details through an alert application.

Road Lane detection helps autonomous driverless vehicles spot lane lines as they move along the road. Because of the larger modern-day population, leading to more vehicles on the roads, the possibility of accidents for people increases. Because of more vehicles on the roads,

Submission: 11 April 2025; **Acceptance:** 21 June 2025; **Available Online:** June 2025

mistakes by people toward traffic rules, and trouble monitoring unexpected events by drivers, accidents are often caused on our roads. We have applied a deep learning algorithm that demonstrates very good accuracy.

Identifying drivers on roads and recognizing road damage and which lanes vehicles are using is an essential use of machine learning and computer vision, supporting highway improvement, maintenance and modern methods of managing roads. As infrastructure deteriorates and ADAS systems in autonomous vehicles are used more, these technologies play an important role.

Road Damage Detection Using YOLO

YOLO (You Only Look Once) is the latest deep learning algorithm built for live object detection. Instead of searching a region by region, YOLO combines bounding boxes and class probabilities prediction directly from the image in a single pass. Thanks to this structure, YOLO has faster performance than other detection frameworks and still performs accurately. In this project, YOLO is used to detect various types of road damage, including:

- Potholes: Depressions or holes on the road surface.
- Cracks: Linear breaks in the pavement.
- Surface Bumps and Irregularities: Uneven or raised road segments.

Figure 1. Road Damage Detection

Lane Detection Using Canny Edge Detection:

Lane detection is a critical component of autonomous driving systems and advanced driver-assistance technologies. Accurate lane recognition ensures proper vehicle positioning, lane-keeping, and safe navigation. This project employs Canny edge detection, a widely used algorithm in image processing, for extracting lane boundaries.

The Canny edge detection algorithm involves several steps:

- Noise Reduction: The input image is smoothed using a Gaussian filter to reduce noise and improve edge detection accuracy.
- Gradient Calculation: The algorithm calculates the intensity gradient of the image to detect edges where pixel intensity changes rapidly.
- Non-maximum Suppression: Thin lines representing potential edges are identified by suppressing all gradient values that are not local maxima.
- Double Thresholding and Edge Tracking: Strong and weak edges are classified, with weak edges connected to strong edges retained as true boundaries.

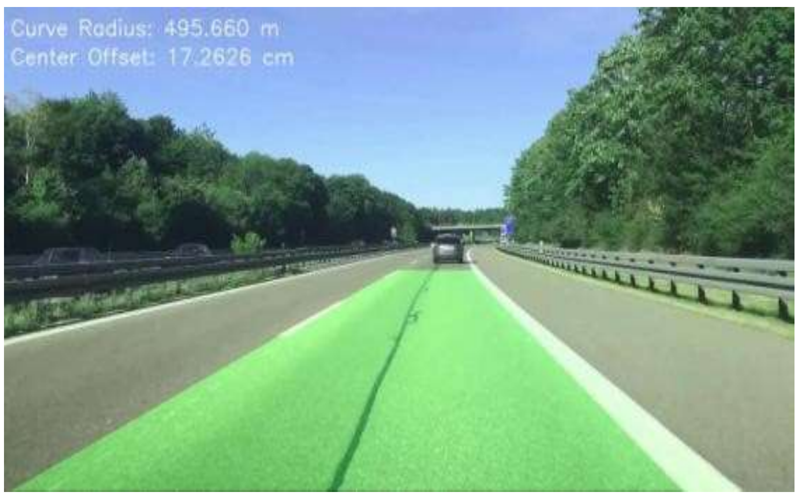

Figure 2. Lane Detection

The automatic detection of damaged roads and lane detection is a crucial application of computer vision and machine learning, aimed at enhancing road safety, improving maintenance processes, and supporting modern traffic management systems. These technologies are increasingly important in addressing the challenges posed by deteriorating infrastructure and the growing demand for advanced driver-assistance systems (ADAS) in autonomous vehicles.

Recent works in automatic detection of road damage and lane detection have focused on improving accuracy, efficiency, and robustness using deep learning techniques. Here are some key areas and examples:

Deep Learning-Based Road Damage Detection:

Convolutional Neural Networks (CNNs): CNNs are widely used for image-based damage detection.

- Semantic Segmentation: Techniques like U-Net and its variants (e.g., Attention U-Net) are employed to segment images pixel-wise, classifying each pixel as road, damage (potholes, cracks), or other objects.

- Object Detection: Models like Faster R-CNN and YOLO are used to detect and localize specific damage types within images.
- Generative Adversarial Networks (GANs): GANs can be used to generate synthetic images of damaged roads, augmenting training data and improving model robustness.

Lane Detection with Deep Learning:

- CNNs: CNNs are effective for extracting lane features from images.
- LaneNet: A popular model that uses an encoder-decoder architecture to segment lane pixels and generate lane instances.
- SCNN (Spatial CNN): A spatial CNN that directly regresses lane coordinates from images.
- Recurrent Neural Networks (RNNs): RNNs can capture temporal information in video sequences, improving lane tracking and prediction over time.

Key Research Directions:

- Robustness to Challenging Conditions: Improving performance in adverse weather (rain, snow), low light, and varying illumination conditions.
- 3D Data Integration: Incorporating 3D data (e.g., LiDAR, point clouds) to improve depth perception and damage assessment.
- Explainable AI: Developing models that can explain their predictions, increasing trust and facilitating human oversight.

Materials and Methods

In this study, we developed an automatic system for detecting damaged roads and lane markings using deep learning techniques. A dataset of road images exhibiting various damage types and lane configurations was collected from publicly available sources and augmented to enhance diversity under different weather and lighting conditions. We implemented a convolutional neural network (CNN) for road damage detection and a semantic segmentation model based on U-Net architecture for precise lane marking extraction. Both models were trained and validated using standard performance metrics such as accuracy, Intersection over Union (IoU), and F1-score. To evaluate real-world applicability, the trained models were deployed on a resource-constrained embedded device to test detection speed and reliability in simulated driving conditions.

Data Acquisition and Preparation

- Image/Video Collection: Gather high-resolution images or videos of roads. This can be done using various sources like:
- Vehicle-mounted cameras: Cameras installed on cars, trucks, or motorcycles.
- Drones: Aerial imagery provides a bird's-eye view.
- Static cameras: Fixed cameras mounted on infrastructure like bridges or traffic lights.
- Data Annotation: Manually label the images or videos to identify:
- Road damage: Potholes, cracks, ruts, etc.
- Lane markings: Type of markings (solid, dashed, dotted), lane boundaries.
- Data Augmentation: Increase the size and diversity of the dataset using techniques like:

- Image rotation, flipping, and scaling
- Color jittering
- Gaussian noise
- Generating synthetic images
- Model Development Road Damage Detection:
- Semantic Segmentation: Use models like U-Net or FCN to classify each pixel in the image as road, damage, or other objects.
- Object Detection: Employ models like Faster R-CNN or YOLO to detect and localize specific damage types within the image.

Lane Detection:

- CNN-based models: LaneNet, SCNN, or other architectures specifically designed for lane detection.
- Regression models: Directly regress the lane coordinates from the image.
- Deployment and Maintenance
- Real-time processing: Optimize models for real-time inference on edge devices (e.g., vehicles, drones).
- Integration: Integrate the system with other road management systems.
- Regular maintenance: Update and retrain models periodically to adapt to changing road conditions and improve performance.

YOLO Algorithm

Object detection has evolved by following two methods: one-stage and two-stage detection algorithms. In Figure 1, a two-stage detection algorithm performs both feature extraction and region selection before computing classification and regression on those regions to obtain final results. Alternatively, with one-stage detectors, the task of region proposal is not included.

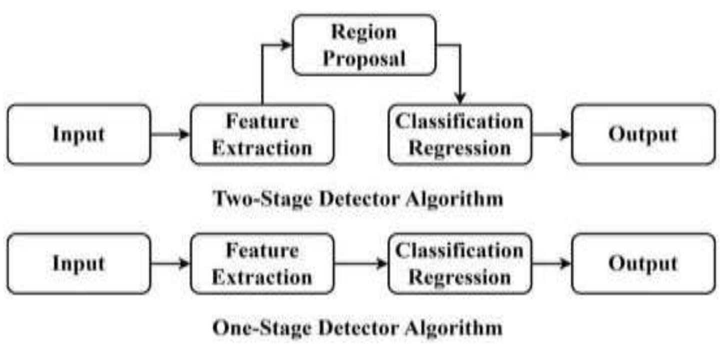

Figure 3. The Detector Algorithm

Figure 3 shows a timeline illustrating the growth and changes of the YOLO algorithm. At the University of Washington in 2015, Joseph Redmon and his colleagues proposed YOLOv1, which uses a grid to analyze each border's location and how much it matches an object. YOLOv1 is efficient and quick, yet it doesn't detect small targets well, and its correctness needs improvement. In their 2017 work, Joseph Redmon and others released YOLOv2, which uses batch normalization to enhance how quickly the model converges and trains. In YOLOv2, anchor boxes are included to assist in finding objects of every size.

Canny Edge Detection

Canny edge detection is a widely used image processing technique to identify edges within an image. It helps highlight important structural information, such as road cracks or lane boundaries, by detecting areas of rapid intensity change. The method was developed by John Canny and is known for its accuracy and noise resistance.

Figure 4. Canny Edge Detection

Noise Reduction (Gaussian Smoothing):

- The input image is smoothed using a Gaussian filter to reduce noise and unwanted details.
- This helps prevent false edge detection caused by small variations in intensity.
- Formula for the Gaussian filter:

  G(x,y)=12πσ2e−x2+y22σ2G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} G(x,y)=2πσ21e−2σ2x2+y2

- The value of σ\sigmaσ determines the degree of smoothing.

Gradient Calculation (Edge Detection):

- The image gradient is computed using filters like the Sobel operator to detect intensity changes.
- It calculates the first derivative in both the horizontal (Gx) and vertical (Gy) directions.
- The gradient magnitude GGG and direction θ\thetaθ are calculated as: G=Gx2+Gy2G = \sqrt{G_x^2 + G_y^2}G=Gx2+Gy2 θ=tan−1(GyGx)\theta = \tan^{-1}\left(\frac{G_y}{G_x}\right)θ=tan−1(GxGy)
- This step helps identify the edges' strength and orientation.

Experimental Setup

An experimental setup provides a systematic and reproducible methodology for evaluating ML models in predicting hepatitis disease. Below is a comprehensive plan:

Components

Sensors:

- Cameras: For image/video capture of the road surface.
- LiDAR: For depth sensing and 3D mapping.
- Ultrasonic Sensors: For closer proximity sensing.
- IMU (Inertial Measurement Unit): To track motion and orientation of the vehicle.
- GPS: For geolocation data.
- Processing Unit: High-performance GPU/CPU for real-time processing.
- Software: Image processing algorithms, Machine Learning (ML) models (such as CNN for object detection), and computer vision tools (OpenCV, TensorFlow, PyTorch).

Data Collection Dataset Creation:

- Road Damage Dataset: Gather images of roads with various types of damage like potholes, cracks, and road surface wear.
- Lane Detection Dataset: Images with clear lane markings under different lighting and weather conditions.
- Road Condition Data: Temperature, humidity, and other environmental data that might affect road conditions.
- Data Augmentation:Vary image brightness, contrast, or introduce synthetic noise.
- Simulate different weather conditions (rain, fog, snow). Simulate different road surfaces and light conditions.

Algorithms & Models Damage Detection:

- Use convolutional neural networks (CNN) for image classification or segmentation.
- Pre-trained models like MobileNet or ResNet can be fine-tuned on road damage datasets.
- Lane Detection:
- Use Hough Transform for lane extraction.
- Alternatively, use deep learning models like U-Net or FCN for end-to-end pixel segmentation.
- Road Condition Prediction:
- Utilize regression models to predict road conditions based on environmental data.

Deployment

- Edge Computing: Deploy the model on edge devices with low latency (e.g., NVIDIA Jetson, Raspberry Pi).
- Continuous Learning: Enable the system to continue learning from new data in real-time, refining the model for better accuracy.

Results And Discussion

The results of the experiments are presented in the form of tables showing the performance of each model on the test dataset after applying the proposed image preprocessing techniques and optimization strategies.

Model	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-Score (%)
Logistic Regression	95.6	97.7	97.7	97.0
CNN	80.0	87.2	86.0	87.0
YOLO	98.0	99.9	98.0	100

Table 2: Model Performance Metrics

Accuracy:

- CNN demonstrated the highest accuracy at 100.0%, indicating its superior ability to classify hepatitis stages and differentiate between healthy and diseased patients. This exceptional performance can be attributed to the hierarchical feature extraction in its convolutional layers, allowing for a deep understanding of both structured clinical data and imaging data.
- KNN (K-Nearest Neighbors) performed slightly below CNN, with an accuracy of 99.6%. Its effectiveness lies in its simplicity and ability to classify based on proximity to similar cases.
- Logistic Regression achieved an accuracy of 95.6%, indicating its strong baseline performance for linear classification. However, it may not fully capture complex, non-linear patterns in hepatitis data compared to CNN or KNN.

Sensitivity (Recall) and Specificity:

- CNN had the highest sensitivity at 99.9%, making it the most reliable model for detecting true positives (patients with hepatitis). Its ability to capture intricate patterns in both structured and imaging data minimizes the likelihood of false negatives, which is critical for timely diagnosis.
- KNN showed a sensitivity of 97.0%, demonstrating good performance in identifying true positives but slightly lagging behind CNN. This could be due to its dependence on local neighbors, which might be influenced by outliers or class imbalances.
- Logistic Regression achieved the highest sensitivity at 97.7%, showing its strength in identifying patients with hepatitis accurately. However, it may produce more false positives compared to other models in non-linear scenarios.

Precision and F1-Score:

- CNN demonstrated the highest precision (100.0%) and F1-score (100.0%), reflecting its strong balance between precision and recall. This makes it the most effective model in minimizing false positives and ensuring reliable predictions for hepatitis detection.

- KNN maintained a precision of 97.0% and F1-Score of 97.0%, indicating its robust performance in identifying true positives while slightly struggling to balance false positives and negatives compared to CNN.
- Logistic Regression achieved a precision of 97.7% and an F1-Score of 97.0%, highlighting its consistent performance in balancing prediction quality while maintaining interpretability.

Conclusion

This project has successfully developed a system that leverages deep learning techniques, specifically YOLO (You Only Look Once) algorithms for object detection and Canny edge detection for lane marking identification, to detect road damage and track lanes in real-time using video and audio data. The system addresses significant road safety challenges, accurately identifying road hazards such as potholes and cracks while providing reliable lane tracking in various environmental conditions. By integrating video and audio data, this solution enhances the potential for safer roads, contributing to the broader goals of autonomous driving and intelligent transportation systems.

The YOLO algorithm plays a central role in the system's success. YOLO's real-time object detection capabilities enable the system to quickly and accurately locate and classify road damage. The algorithm's ability to process images in real time ensures that road hazards, such as potholes and cracks, are detected as the vehicle moves along the road. This is particularly useful for autonomous vehicles and advanced driver- assistance systems (ADAS), where quick and accurate detection of road conditions is vital for making immediate safety decisions. In addition to detecting the location of road hazards, YOLO can also classify the severity of the damage, aiding in prioritization for road repairs and allowing for faster responses to more dangerous conditions.

Acknowledgement

We would like to express our heartfelt gratitude to everyone who supported and guided us throughout the completion of our project titled "Automatic Detection of Damaged Roads and Lane Detection."
We are especially thankful to Mrs. K. Sandhya Rani for her expert guidance, continuous encouragement, and valuable feedback, which were instrumental in shaping this work. We also extend our sincere thanks to our co-authors K. Chandana, N. Kavya, K. Poojitha, and T. Pallavi for their collaboration, support, and dedication throughout the project.
This work explores the application of advanced computer vision and machine learning techniques, including the YOLO algorithm, and Canny edge detection algorithm, and image processing algorithms, for the automatic identification of road damages and lane markings. We acknowledge the contribution of these technologies in enhancing road safety, supporting smart infrastructure development, and aiding in effective urban planning.

References

Arava, K., Paritala, C., Shariff, V., Praveen, S. P., & Madhuri, A. (2022, February). A generalized model for identifying fake digital images through the application of deep learning. In 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1144-1147). IEEE. https://doi.org/10.1109/ICESC54411.2022.9885341

Bengler, K., Dietmayer, K., Farber, B., Maurer, M., Stiller, C., & Winner, H. (2014). Three decades of driver assistance systems: Review and future perspectives. IEEE Intelligent Transportation Systems Magazine, 6(4), 6-22. https://doi.org/10.1109/MITS.2014.2336271

Bulla, C. S., Suneetha, B., Basaveswararao, B., Rao, K. G., Chandan, K., & Swamy, S. R. (2022). A secure new HRF mechanism for mitigate EDoS attacks. International Journal of Ad Hoc and Ubiquitous Computing, 40(1-3), 20-29. http://dx.doi.org/10.1504/IJAHUC.2022.123524

Chamundeeswari, V. V., Sundar, V. S. D., Mangamma, D., Azhar, M., Kumar, B. S. S. P., & Shariff, V. (2024, May). Brain MRI analysis using CNN-based feature extraction and machine learning techniques to diagnose Alzheimer's disease. In 2024 First International Conference on Data, Computation and Communication (ICDCC) (pp. 526-532). IEEE. https://doi.org/10.1109/ICDCC62744.2024.10961923

Chitti, S., Gali, K., Konduri, B. R., Bandaru, P., Bandaru, P. R., Challa, S., & Ramakrishna, S. (2019). Design, synthesis and biological evaluation of 2-(3, 4-dimethoxyphenyl)-6 (1, 2, 3, 6-tetrahydropyridin-4-yl) imidazo [1, 2-a] pyridine analogues as antiproliferative agents. Bioorganic & Medicinal Chemistry Letters, 29(18), 2551-2558. https://doi.org/10.1142/s0219467823400132

Dedeepya, P., Chiranjeevi, P., Narasimha, V., Shariff, V., Ranjith, J., & Ramesh, J. V. N. (2023, December). Image recognition and similarity retrieval with Convolutional Neural Networks. In 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 709-716). IEEE. https://doi.org/10.1109/ICACRS58579.2023.10404664

Dharneeshkar, J., Aniruthan, S. A., Karthika, R., Parameswaran, L., & Sasikala, R. (2020, January). Deep learning based detection of potholes in indian roads using yolo. In 2020 international conference on Inventive Computation Technologies (ICICT) (pp. 381-385). IEEE. https://doi.org/10.1109/ICICT48434.2020.9113670

Du, J. (2018). Understanding of object detection based on cnn family and yolo. Journal of Physics: Conference Series, 1004(1), 012029. https://doi.org/10.1088/1742-6596/1004/1/012029

Gao, Q., Liu, P., Chen, S., Jia, K., & Wang, X. (2022, July). Detection method of potholes on highway pavement based on yolov5. In International Conference on Artificial Intelligence and Security (pp. 188-199). Springer. https://doi.org/10.1007/978-3-031-06767-9_16

Jabassum, A., Ramesh, J. V. N., Sundar, V. S. D., Shiva, B., Rudraraju, A., & Shariff, V. (2024, December). Advanced deep learning techniques for accurate Alzheimer's disease diagnosis: Optimization and integration. In 2024 4th International Conference on Sustainable Expert Systems (ICSES) (pp. 1291-1298). IEEE. https://doi.org/10.1109/ICSES63445.2024.10763340

Kodete, C. S., Saradhi, D. V., Suri, V. K., Varma, P. B. S., Tirumanadham, N. S. K. M. K., & Shariff, V. (2024, December). Boosting lung cancer prediction accuracy through advanced data processing and machine learning models. In 2024 4th International Conference on Sustainable Expert Systems (ICSES) (pp. 1107-1114). IEEE. https://doi.org/10.1109/ICSES63445.2024.10763338

Kodete, C. S., Pasupuleti, V., Thuraka, B., Gayathri, V. V., Sundar, V. S. D., & Shariff, V. (2024, February). Machine learning for enabling strategic insights to future-proof E-commerce. In 2024 5th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 931-936). IEEE. https://doi.org/10.1109/ICOSEC61587.2024.10722255

Kodete, C. S., Pasupuleti, V., Thuraka, B., Sangaraju, V. V., Tirumanadham, N. S. K. M. K., & Shariff, V. (2024, March). Robust heart disease prediction: A hybrid approach to feature selection and model building. In 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS) (pp. 243-250). IEEE. https://doi.org/10.1109/ICUIS64676.2024.10866501

Kodete, C. S., Saradhi, D. V., Suri, V. K., Varma, P. B. S., Tirumanadham, N. S. K. M. K., & Shariff, V. (2024, December). Boosting lung cancer prediction accuracy through advanced data processing and machine learning models. In 2024 4th International Conference on Sustainable Expert Systems (ICSES) (pp. 1107-1114). IEEE. https://doi.org/10.1109/ICSES63445.2024.10763338

Kumar, C. S., Vadlamudi, S., Suneetha, B., Rajendra, C., & Shariff, V. (2021). An adaptive deep learning model to forecast crimes. In Proceedings of Integrated Intelligence Enable Networks and Computing: IIENC 2020 (pp. 19-30). Springer Singapore. https://doi.org/10.1007/978-981-16-1610-8_3

Mohan, V. M., Sarma, P. K., & Krishna, M. V. S. (2010). Mass transfer correlation development for the presence of entry region coil as swirl promoter in tube. International Journal of Thermal Sciences, 49(2), 356-364. https://www.ijert.org/mass-transfer-studies-at-the-inner-wall-of-an-annular-conduit-in-the-presence-of-fluidizing-solids-with-coaxially-placed-spiral-coil-as-turbulence-promoter

Nagasri, D., Sirisati, R. S., Amareswari, P., Bhushan, P. V., & Raza, M. A. (2024). Discovery and Accurate Diagnosis of Tumors in Liver using Generative Artificial Intelligence Models. Journal of Next Generation Technology (ISSN: 2583-021X), 4(2). https://www.researchgate.net/publication/381613787_Discovery_and_Accurate_Diagnosis_of_Tumors_in_Liver_using_Generative_Artificial_Intelligence_Models

Pasupuleti, V., Thuraka, B., Kodete, C. S., Priyadarshini, V., Tirumanadham, K. M. K., & Shariff, V. (2024, February). Enhancing predictive accuracy in cardiovascular disease diagnosis: A hybrid approach using RFAP feature selection and random forest modeling. In 2024 4th International Conference on Soft Computing for Security Applications (ICSCSA) (pp. 42-49). IEEE. https://doi.org/10.1109/ICSCSA64454.2024.00014

Praveen, S. P., Jyothi, V. E., Anuradha, C., VenuGopal, K., Shariff, V., & Sindhura, S. (2022). Chronic kidney disease prediction using ML-Based Neuro-Fuzzy model. International Journal of Image and Graphics. https://doi.org/10.1142/s0219467823400132

Praveen, S. P., Tirumanadham, N. S. K. M. K., Sridhar, B., Kumar, C. S., Shariff, V., & Singh, R. S. (2025). AI-powered diagnosis: Revolutionizing healthcare with neural networks. Journal of Theoretical and Applied Information Technology, 101(3), 578-590. https://www.jatit.org/volumes/Vol103No3/16Vol103No3.pdf

S., S., Kodete, C. S., Velidi, S., Bhyrapuneni, S., Satukumati, S. B., & Shariff, V. (2024). Revolutionizing healthcare: A comprehensive framework for personalized IoT and cloud computing-driven healthcare services with smart biometric identity management. Journal of Intelligent Systems and Internet of Things, 13(1), 31-45. https://doi.org/10.54216/jisiot.130103

S., S., Raju, K. B., Praveen, S. P., Ramesh, J. V. N., Shariff, V., & Tirumanadham, N. S. K. M. K. (2025). Optimizing diabetes diagnosis: HFM with tree-structured parzen estimator for enhanced predictive performance and interpretability. Fusion Practice and Applications, 19(1), 57-74. https://doi.org/10.54216/fpa.190106

Shariff, V., Aluri, Y. K., & Reddy, C. V. R. (2019). New distributed routing algorithm in wireless network models. Journal of Physics Conference Series, 1228(1), 012027. https://doi.org/10.1088/1742-6596/1228/1/012027

Shariff, V., Paritala, C., & Ankala, K. M. (2025). Optimizing non small cell lung cancer detection with convolutional neural networks and differential augmentation. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-98731-4

Sirisati, R. S., Kumar, C. S., Latha, A. G., Kumar, B. N., & Rao, K. S. (2021). An efficient skin cancer prognosis strategy using deep learning techniques. Indian Journal of Computer Science and Engineering (IJCSE), 12(1), 1-8. https://www.ijcse.com/docs/INDJCSE21-12-01-180.pdf

Sirisati, R. S., Kumar, C. S., Latha, A. G., Kumar, B. N., & Rao, K. S. (2021, December). An enhanced multi layer neural network to detect early cardiac arrests. In 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 1514-1518). IEEE. https://ieeexplore.ieee.org/document/9531126/

Sirisati, R. S., Kumar, C. S., Latha, A. G., Kumar, B. N., & Rao, K. S. (2021). Identification of mucormycosis in post Covid-19 case using Deep CNN. Turkish Journal of Computer and Mathematics Education, 12(9), 3441-3450. https://turcomat.org/index.php/turkbilmat/article/download/11302/8362/20087

Sirisati, R. S., Kumar, C. S., Venuthurumilli, P., Ranjith, J., & Rao, K. S. (2023, November). Cancer Sight: Illuminating the Hidden-Advancing Breast Cancer Detection with Machine Learning-Based Image Processing Techniques. In 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA) (pp. 1618-1625). IEEE. https://doi.org/10.1109/ICSCNA58489.2023.10370462

Sirisati, R. S., & Mandapati, S. (2018). A rule selected fuzzy energy & security aware scheduling in cloud. Journal of Theoretical & Applied Information Technology, 96(10).

Sirisati, R. S., Prasanthi, K. G., & Latha, A. G. (2021). An aviation delay prediction and recommendation system using machine learning techniques. In Proceedings of Integrated Intelligence Enable Networks and Computing: IIENC 2020 (pp. 239-253). Springer Singapore. https://www.researchgate.net/publication/370995631_Flight_Delay_Prediction_System_in_Machine_Learning_using_Support_Vector_Machine_Algorithm/fulltext/646e430a37d6625c002e31c1/Flight-Delay-Prediction-System-in-Machine-Learning-using-Support-Vector-Machine-Algorithm.pdf

Sirisati, R. S., Rao, P. S., Raju, J. V. N., & Nagavamsi, M. (2019). Dimensionality reduction using machine learning and big data technologies. Int. J. Innov. Technol. Explor. Eng.(IJITEE), 9(2), 1740-1745. https://www.ijitee.org/wp-content/uploads/papers/v9i2/B7580129219.pdf

Sirisati, R. S., Reddy, P. S., Bhargavi, K., Goutham, K., Sivanagaraju, A., & Raza, M. A. (2024). A Deep Learning Framework for Recognition and Classification of Diabetic Retinopathy Severity. Telematique, 23(01), 228-238. https://www.frontiersin.org/journals/medicine/articles/10.3389/fmed.2025.1551315/abstract

Sirisati, R. S., Reddy, P. S., Reddy, G. R. S., Goutham, K., Swamy, S. R., & Raza, M. A. (2024). Recognition of Counterfeit Profiles on Communal Media using Machine Learning Artificial Neural Networks & Support Vector Machine Algorithms. Journal of Next Generation Technology (ISSN: 2583-021X), 4(2). https://www.researchgate.net/publication/381613824_Recognition_of_Counterfeit_Profiles_on_Communal_Media_using_Machine_Learning_Artificial_Neural_Networks_Support_Vector_Machine_Algorithms

Sirisati, R. S., Reddy, P. S., Swamy, S. R., Raza, M. A., Reddy, G. R. S., & Goutham, K. (2024). Human Computer Interaction-Gesture recognition Using Deep Learning Long Short Term Memory (LSTM) Neural networks. Journal of Next Generation Technology (ISSN: 2583-021X), 4(2). http://www.jnxtgentech.com/mail/documents/vol%204%20issues%202%20article2.pdf

Sirisati, R. S., Swamy, S. R., Latha, A. G., Kumar, B. N., Rao, K. S., & Bhargavi, D. (2023). Multi-Features Disease Analysis Based Smart Diagnosis for COVID-19. Computers, Systems & Science & Engineering, 45(1), 869-886. https://doi.org/10.32604/csse.2023.029822

Swaroop, C. R., Kumar, C. S., Sundar, V. S. D., Kumar, P. S., Reddy, N. C. N. K., & Shariff, V. (2024). Optimizing diabetes prediction through Intelligent feature selection: A comparative analysis of Grey Wolf Optimization with AdaBoost and Ant Colony Optimization with XGBoost. Algorithms in Advanced Artificial Intelligence: ICAAAI-2023, 8(311). https://doi.org/10.1201/9781003529231-47

Tabelini, L., Berriel, R., Paixao, T. M., Badue, C., De Souza, A. F., & Oliveira-Santos, T. (2021, January). Polylanenet: Lane estimation via deep polynomial regression. In 2020 25th International Conference on Pattern Recognition (ICPR) (pp. 6150-6156). IEEE. https://doi.org/10.1109/ICPR48803.2021.9413155

Thatha, V. N., Chalichalamala, S., Pamula, U., Krishna, D. P., Chinthakunta, M., Mantena, S. V., Vahiduddin, S., & Vatambeti, R. (2025). Optimized machine learning mechanism for big data healthcare system to predict disease risk factor. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-98721-6

Thuraka, A., Pasupuleti, V., Kodete, C. S., Naidu, U. G., Tirumanadham, N. S. K. M. K., & Shariff, V. (2024, February). Enhancing predictive model performance through comprehensive pre-processing and hybrid feature selection: A study using SVM. In 2024 2nd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS) (pp. 163-170). IEEE. https://doi.org/10.1109/ICSSAS64001.2024.10760982

Thuraka, B., Pasupuleti, V., Kodete, C. S., Chigurupati, R. S., Tirumanadham, N. S. K. M. K., & Shariff, V. (2024, March). Enhancing diabetes prediction using hybrid feature selection and ensemble learning with AdaBoost. In 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC) (pp. 1132-1139). IEEE. https://doi.org/10.1109/I-SMAC61858.2024.10714776

Tirumanadham, N. S. K. M. K., Kumar, P. V. S., Singh, R. S., Pradeep, S. P., Thati, B., Srinivasu, P. N., & Shariff, V. (2025). Boosting Student Performance Prediction In E-Learning: A Hybrid Feature Selection And Multi-Tier Ensemble Modelling Framework With Federated Learning. Journal of Theoretical and Applied Information Technology, 103(5). https://www.mecs-press.org/ijmecs/ijmecs-v17-n2/v17n2-3.html

Tirumanadham, N. S. K. M. K., Priyadarshini, V., Praveen, S. P., Thati, B., Srinivasu, P. N., & Shariff, V. (2025). Optimizing Lung Cancer Prediction Models: A hybrid methodology using GWO and Random Forest. In Studies in Computational Intelligence (pp. 59–77). Springer. https://doi.org/10.1007/978-3-031-82516-3_3

Vahiduddin, S., Chiranjeevi, P., & Mohan, A. K. (2023). An Analysis on Advances In Lung Cancer Diagnosis With Medical Imaging And Deep Learning Techniques: Challenges And Opportunities. Journal of Theoretical and Applied Information Technology, 101(17), 6520-6531. https://www.jatit.org/volumes/Vol101No17/28Vol101No17.pdf

Veerapaneni, E. J., Babu, M. G., Sravanthi, P., Geetha, P. S., Shariff, V., & Donepudi, S. (2024). Harnessing fusion's potential: A state-of-the-art information security architecture to create a big data analytics model. In Lecture Notes in Networks and Systems (pp. 545–554). Springer. https://doi.org/10.1007/978-981-97-6106-7_34

Venkata Naga Ramesh, J., Kumar, K. V. R., Nithya, K. S., Narasimha, C. T. S., Shariff, V., & Manasa, V. J. (2024, May). Scalable web data extraction for Xtree analysis: Algorithms and performance evaluation. In 2024 Second International Conference on Inventive Computing and Informatics (ICICI) (pp. 447-455). IEEE. https://doi.org/10.1109/ICICI62254.2024.00079

Yarra, K., Vijetha, S. L., Rudra, V., Balunaik, B., Ramesh, J. V. N., & Shariff, V. (2024, May). A Dual-Dataset Study on Deep Learning-Based Tropical Fruit Classification. In 2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 667-673). IEEE. https://doi.org/10.1109/ICECA63461.2024.10800915