CAR DAMAGE DETECTION USING CNN

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Abstract - In today's modern society, automobiles playa crucial role, and the automatic classification of car damages holds particular significance for the auto insurance industry. Our proposed solution involves the implementation of two Convolutional Neural Network (CNN) models. Specifically, the VGG16 model is employed to identify and assess the location and severity of car damage, while the Mask R-CNN is utilized to accurately mask the damaged regions. Both models collectively provide valuable insights into the extent.

The CNN models effectively filter out images without damages, allowing only those with identified damage to be passed on to the object detection model. This strategic approach enhances the overall performance of the model. The core objective of this research project is to achieve maximum
accuracy through the utilization of CNN models. TensorFlow,

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1.INTRODUCTION

People's safety and property can only be saved if the fire alarm signal is precisely detected and identified as early as possible in the fire, which is a terrible catastrophe for the security of people's lives and properties. Fire detection accuracy and validity are An a pre-trained framework, was employed in the development of the object detection model, emphasizing efficiency and reliability in the insurance claims process. of damage to a car, enabling insurance companies to expedite claims processing without the need for time-consuming and resource-intensive manual verificationcreated by gathering Internet resources and fire videos shot by the user, and the trained support vector machine was evaluated. The results of the tests revealed that the algorithm can identify early fires more effectively. The model's experimental findings on our dataset reveal that it has good fire detection capability and can identify multi-scale fire in real-time.

An algorithm for the detection of onedimensional fire space is provided to demonstrate the suggested method's fine fault tolerance, robustness, and accuracy in a novel technique for detecting uncertainty fire signals based on fire scenarios. First, an analysis of fire scenario performance yields a fractal character for the fire space, and then an intelligent method based on rough set theory and trend integration is used to process the multi-source signal obtained from a group of fire detectors. When a relationship between the two characters is recognised as being logically coincident, an actual alarm for a fire is triggered.

In recent years, with the development of deep learning and machine vision, it is possible to perform road damage tasks efficiently with road images [1] [2]. Compare with complicated sensors, the deep learning methods are cheaper which only needs to collect images by normal cameras or smartphones installed in the car A lot of studies and researches show that deep convolutional neural networks (CNN) have great success in many vision tasks like image classification, object detection, semantic segmentation, and so on [5] Deep networks can perform object detection and recent approaches can perform real-time detection with the help of GPUs.

2. LITERATURE SURVEY

Ke Chen, Yanying Cheng, Hui Bai , Chunjie Mou, Yuchun Zhang " Research on Image Fire Detection Based on Support Vector Machine." [1] There are a number of environmental factors that must 1 be taken into consideration when using traditional temperature and smoke sensors to spot early fires. A support vector machine-based image fire detection method is created by studying the attributes of fire in digital pictures. Using the inter-frame difference method, the motion zone is identified as the Suspected fire area. One additional sample is taken to ensure the uniformity of the size. Once these features have been gathered, a support vector machine is utilised to identify and categorise objects based on their coloration and texture. Internet resources and self shot videos were combined to form data sets, which were then tested by a trained support vector machine. As a consequence of the trials, the algorithm was 1 shown to be more accurate in spotting fires at an early stage.

Shixiao wu , Libing Zhang," Secure and Efficient Data Deduplication in JointCloud Storage." [2] — Real time detection, early detection, and incorrect detection are the subject of this study. To better detect forest fir this work makes use of faster R-CNN, YOLO (yolov.2.0 and yolov3), and SSD. Increased detection accuracy and faster fire detection are only two of the benefits of employing SSDs in real-world applications. To reduce false alarms, we may use the newly implemented improvements to smoke class and fire area. As we continue to work on the song, we've made some changes to the original tiny-yolo-voc structure and offered a new one. Fire detection accuracy has been proven to be improved by using tiny-yolo voc1. If you want to keep tabs on forest safety and health in real time, this piece is a must have.

HUANG HONGYU1, KUANG PING1, LI FAN1, SHI HUAXIN1 ," AN IMPROVED MULTI-SCALE FIRE DETECTION METHOD BASED ON CONVOLUTIONAL NEURAL NETWORK" To minimize financial damages and environmental damage, fire detection systems must be as accurate as possible and respond as quickly as possible when a fire breaks out. For distant high-dome or early-stage low-flame fires, traditional sensors are still extensively deployed, but their performance is poor, hence image- and video- based methods of predicting fires are becoming more prevalent. This study improves the YOLOv4 1 fire detection system by using Convolutional Neural Networks (CNN). An improved loss function for small- scale flame detection, a combination of Soft-NMS postprocessing and DIoUNMS post-processing to increase the suppression impact of the redundant Bounding box, as well as a reduction in poor recall rate are some of the advantages of our approach. As shown by the model's results on our dataset.

3. PROPOSED SYSTEM

In the recommended system, we employ the AES method for encryption and decryption, as well as data protection and secure access control. The MD 5 technique should be used to prevent duplication of data.

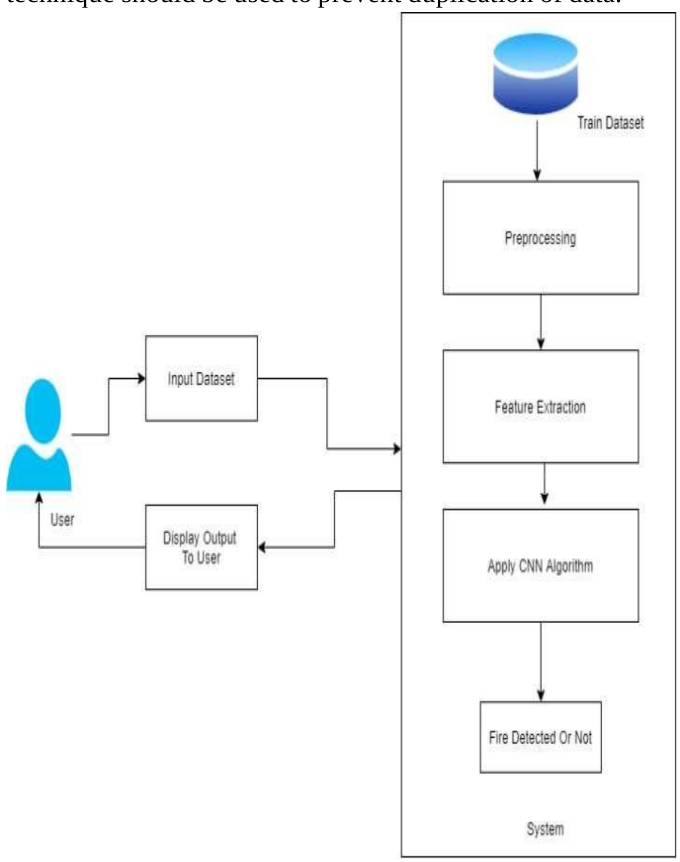


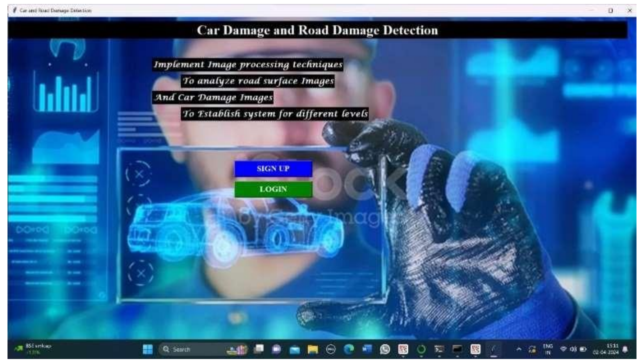
Fig 1:- System Architecture

4. ALGORITHM

The CNN Algorithm was utilised. CNN is a very effective image processing technology. These technologies are presently the best we have for automated image processing. Many organisations use these algorithms to do tasks like detecting things in an image. The RGB colour space is used to store data in images. Matplotlib may be used to read an image from a file and load it into memory. Instead of seeing a visual, the computer sees a sequence of numbers. Color pictures are stored in three-dimensional arrays. The first two dimensions of a picture are its height and breadth (the number of pixels). The last dimension represents 1 the red, green, and blue colours of each pixel Image and video recognition using CNN Convolutional Neural Networks with three layers. Image identification, object recognition, and segmentation are the most common image analysis tasks for which CNN is utilised. 1 Convolutional Neural Networks use three different sorts of layers: 1) Convolutional Layer: This is a layer that uses convolutional neural networks to Each input neuron is linked to the next hidden layer in a typical neural network. Only a tiny percentage of input layer neurons communicate with hidden layer neurons in CNN. 2) The dimensionality 2 of the feature map is determined by the pooling layer. Inside the CNN's buried layer, there will be several activation and pooling layers. The network's ultimate tiers are Fully Connected Levels. The output of the final Pooling or Convolutional Layer is flattened and sent into the fully connected layer as the input of the totally connected layer.

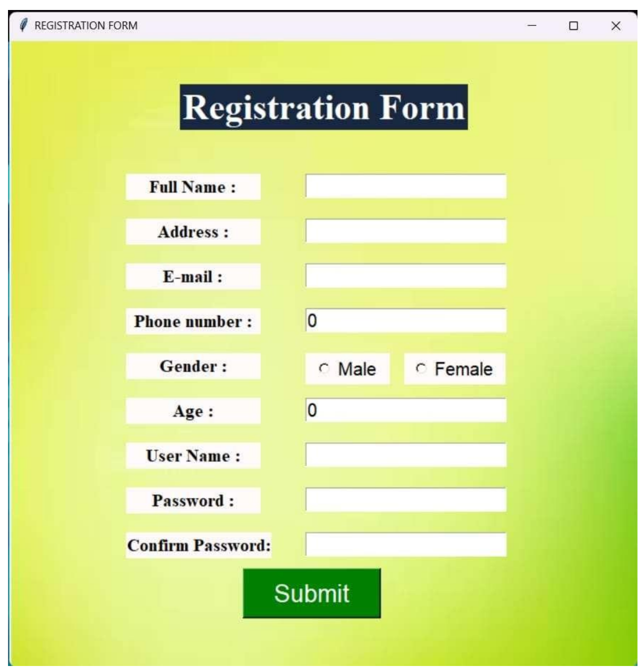
5. IMPLEMENTATION

1. Login and Signup



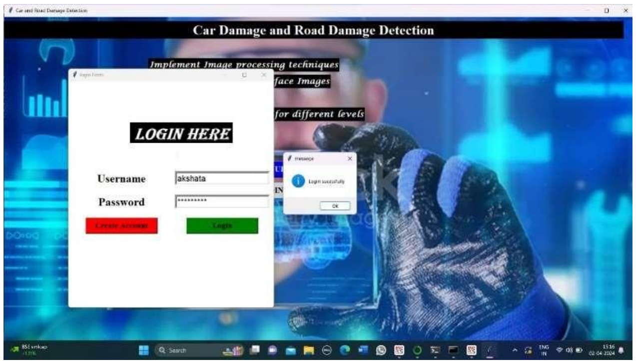
2. Registration Page

A registration page in a car detection system typically refers to a web page or interface where users can sign up or register for an account to access the features and functionalities of the system.



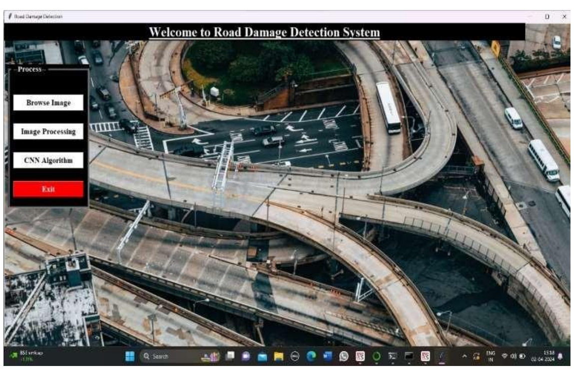
1. Login Page

A login page in a car detection system serves as the initial point of entry for users to access the system.



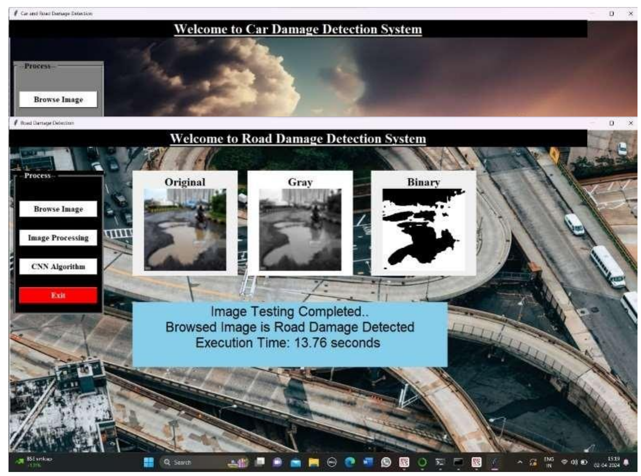
2. Road Damage Detection

A road damage detection page in a car detection system typically refers to a feature or component within a larger system that is designed to identify and analyze road conditions for any signs of damage or hazards. This system is often integrated into advanced driver assistance systems (ADAS) or autonomous vehicle platforms to enhance safety and improve driving efficiency.

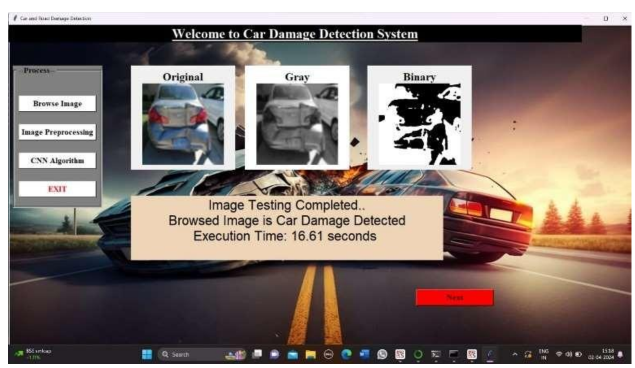


3. Car Damage Detection

A "car damage detection page" in a car detection system typically refers to a user interface or dashboard within the system that is designed to identify and assess any damage to vehicles. This page is usually part of a broader car detection system, which utilizes computer vision and machine learning algorithms to detect and analyze vehicles in images or video footage.



4. Actual Output



CONCLUSION

As a consequence of smart cameras' inbuilt processing capabilities, intelligent surveillance systems have arisen. These intelligent cameras can detect a wide range of unusual events, including vehicle accidents, medical problems, and fires. Fire is the most deadly abnormal occurrence because its failure to be controlled at an early stage may result in huge catastrophes, resulting in human, ecological, and economic losses.

REFERENCES

1. R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierar chies for accurate object detection and semantic segmentation,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2020, vol. 13, no. 1,pp. 580–587.

2. R. Girshick, “Fast R-CNN,” in Proc. IEEE Int. Conf. Comput. Vis.(ICCV), Dec. 2015. pp. 1440–1448.

3. S. Ren, K. He, R. Girshick, and J. Sun, “Faster R CNN: Towards real time object detection with region proposal networks,” IEEE Trans. Pat tern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, Jun. 2021, doi: 10.1109/tpami.2016.2577031

4. W. Liu, D. Anguelov, and D. Erhan, “SSD: Single shot multibox detec tor,” in Proc. IEEE Eur. Conf. Comput. Vision, Jun. 2020, pp. 21–37

5. K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for im age recognition,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2021, pp.770–778.

6. Y. Liu, P. Zhang, Q. Song, A. Li, P. Zhang, and Z. Gui, “Automatic seg mentation of cervical nuclei based on deep learning and a conditional random field,” IEEE Access, vol. 6, pp. 53709–53721, 2020

7. G. Han, J. Su, and C. Zhang, “A method based on multi-convolution lay ers joint and generative adversarial networks for vehicle detection,” in Proc. KSII Trans. Internet Inf. Syst., 2019, pp. 1795–1811.

8. A. Mathew, J. Mathew, M. Govind, and A. Mooppan, “An improved transfer learning approach for intrusion detection,” Procedia Comput. Sci., vol. 115, pp. 251– 257, Jan. 2020

9. T.-Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, and S. Belongie,“Feature pyramid networks for object detection,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jul. 2020, pp. 320–329.

10. R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierar chies for accurate object detection and semantic segmentation,” in Proc.IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2021, vol. 13, no. 1,pp. 580–587