iJRASET

International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: III Month of publication: March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78740

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Traffic Sign Recognition System

A.R.Gadge[1], Tanay Sawant[2], Aditya Shelke[3], Abhang Shirke[4], Abhishek Varale[5]
[1]Staff, [2, 3, 4, 5]Student, Department of Computer Engineering, AISSMS Polytechnic College, Pune, Maharashtra, India

Abstract: ***Trafficsignsrepresentafundamentalcomponentofglobalroadsafetyinfrastructure,communicating critical regulatory, warning, and navigational information. In recent years, the rapid proliferation of Advanced DriverAssistance Systems(ADAS)andtheparadigmshifttowardfullyautonomousvehicleshavefundamentally transformed automotive engineering, drawing significantly more attention to self-driving capabilities than traditional manual operation. Consequently, equipping vehicles with the ability to autonomously perceive and interpret their environment has become a paramount research priority. Traffic Sign Detection and Recognition (TSDR) serves as the crucial cognitive link enabling autonomous systems to comprehend the road ahead and executeinformed,safenavigationaldecisions.Asaresult,ithasemergedasoneofthemostprominentandrapidly evolving domains withincomputer vision andimage processing.This project addresses the inherentcomplexities of dynamic driving environments by developing a robust system designed to continuously detect and recognize traffic signs within live video sequences recorded by an on-board vehicle camera. To achieve this, a Real-Time Traffic Sign Recognition software architecture is formulated, seamlessly integrating Computer Vision preprocessing techniques with state-of-the-art Deep Learning models. Specifically, the system leverages Convolutional Neural Networks (CNNs) optimized for high-accuracy spatial feature extraction and rapid inference.This paper presents a dual-faceted contribution. First, it outlines a comprehensive survey of contemporary methodologies in TSDR, analyzing systems based on both static image and dynamic video data. This review primarily focuses on illustrating prevailing trends and highlighting persistent environmental challenges.***

Index Terms: Real-Time, Traffic Sign Detection and Recognition (TSDR),DeepLearning,ConvolutionalNeural Networks (CNN), Computer Vision, Advanced Driver Assistance Systems (ADAS), TensorFlow.

I. INTRODUCTION

Traffic signs are warning and caution signs that are assigned on roads to advise drivers of road conditions and constraints or the way to go. Problems with road safety are mostly due to driver-specific subjective factors such as negligence and non-compliance with traffic regulations. For these reasons, high-tech cars havelatelybecomeavaluablemethodforeradicatingthesehumanfactors.RT-TSRisthetoolforidentifying traffic signs automatically and it provides the capability for smart cars and smart driving.

An automatic TSDR systemcan detectandcategorize traffic signs withinimages thatare taken by cameras or some imaging sensors. The fundamental objective of this system is to assure drivers' safety by understandingthisvisuallanguageandnotifying thesituationanddirectionoftrafficsandalertingthedriver in any unfavorable condition. To make it easy for drivers to read and recognize, traffic signs are often designed to be of a unique shape and color with symbols inside, so that there is a considerable difference betweenthetrafficsignsandthebackground.Forexample,thespeedlimit60trafficsignisacircularshape with a strong number “60”.

Typically, given a road scene image, TSR automatically localizes and recognizes traffic signs in it, thereby remindinghumandriversorhelpingADASmakedecisions.Thispaperfirstreviewsthemainideasofdeep learning, and displays several related frequently-used algorithms for computer vision. Afterwards, the current research status of computervisionfieldisdemonstratedinthispaper,particularlythemainapplicationsofdeeplearninginthe research field.

Deep learning is an easy way to achieve a good approximation of the complex function by increasing the number of hidden layers. Based on a layer-by-layer training approach [15], human beings can effectively avoid the gradient diffusion by regarding the results of training on the upper layer as the input of the next layer.

Deeplearningalgorithmsare-

- GenerativeAdversarialNetwork(GAN)
- ConvolutionalNeuralNetwork (CNN)
- FullyConvolutionalNetworks (FCN)

Imagerecognitionanddetectionisaclassicmachinelearningproblem.Itisaverychallengingtasktodetectanobjectortorecognizeanimagefro madigitalimageoravideo.Image recognitionhasapplication inthe various field of computer vision, some of which include facial recognition, biometric systems, self-driving cars,emotiondetection,imagerestoration, robotics.

However,therearestillmanychallengingsituationsforrealworldapplications.Detectionofroadscenesisextremelycomplicated,becauseofvaryingillumination, colordeteriorationoftrafficsignsandtheexistenceofdecorationslookingsimilartotrafficsigns.Allthese shortcomings have been covered in detail further in section [IV].

II. LITERATURE REVIEW

Thoroughresearchhasbeendoneintheareaofrecognitionandclassificationoftrafficandroadsigns.Traffic sign detection and recognition based on convolutional neural network proposed a total of 28 signs from different road sign categories such as warning signs, traffic calming signs, speed limit signs, etc. The first step isthe selection of ROI and as the sign is in RGBcolor, theHSV color space method isused to convert from RGB color to HSV image. The shape classifier is also used in this paper to classify the shape as the sign is triangular, circular, and rectangular. Then, 28 signs images are augmented with methods like shear, random rotation, flip, etc. to increase the training sets. The paper has used two CNN neural networks one networkwilltrytoclassify theshapeofthecontour; Theotherneuralnetworkwilltrytoclassifyiftheimage patch contains any sign or not, so if then what is the sign. The categorical entropy method was used to find the lossofthenetworks.Addeltaoptimizer wasusedtoachieve convergence. Themodelistestedfromthe testdatasetthatconsistsofUkrainianandBangladeshtrafficsigns.Thetotalaccuracyofthisnetworkis90% and
on Traffic Sign Detection Based on Convolutional Neural Network uses the TT100K (Tsinghua-Tencent 100K) dataset to evaluate the method used. Here the traffic sign detection and classification are done by usingtheimproved RPNnetwork, andbatchnormalizationinconvolutionallayerswithanaccuracyof85% in Thereisplentyofliteratureon TSRissues, andsomereview articlesare available. Foritshighprecisionand accuracy, CNN has been widely accepted in object detection. Extremely promising performances and guaranteeing results have been obtained in TSR with the latest technology methods such as DL and CV. However, these methods still need to be improved to meet the requirements of applications for Real-Time (RT). On the other hand, most of these studies are software, coding, algorithm, and method-based improvementstudies without implementation. Thesestudiesonhowtooperatethesetechniquesin RTTSRsystemsandhowtoadaptthemtoembeddedsystemsareveryfewandinsufficient.Forexample,thepoint- likenoisealgorithmwasdescribedin Localizationofobjectscontourswithdifferentscalesinimagesusing Hough transform, the effective adoption of the noise algorithm, handles with the algorithms for detecting andrecognizingtrafficsigns. InTSR,CNNswereusedtoautomaticallylearnfeatureextractionandperformfinalclassification,andanensembleclassifiercomposedofafew CNNshasalsobeensuggested.AvariationoftheCNNandmultilayerperceptronapproachwasappliedtofurtherimprovetheaccuracy,detection,and recognition. Most of such studies have remained at the theoretical level, there are still deficiencies and questionmarks abouthowtoputitintouseinreallifeandhowtodevelophardwaredevices.Therearestill issues regarding the software being developed running at high speed and capacity in computers, reducing thehardwaretomicrolevels, ordevelopingsoftwaresuitableforthehardware.Thepresentworkcontributes to this particular field leading to the development of an RT-TSR system in which hardware and software worktogether. Manyofthepreviousyear's papersdidn't considerdisorientation, variablelightconditionsas a shortcoming. Here we attempt to overcome these issues as well.

III. PROBLEM STATEMENT

While Advanced Driver Assistance Systems (ADAS) and autonomous vehicles require highly reliable Traffic Sign Detection and Recognition (TSDR) to ensure road safety, developing a system that functions accurately in real-world, dynamic driving environments presents significant technical hurdles. Although traditional computer vision models perform adequately on high-resolution static images, they frequently experience severe latency or failure when processing live video sequences from moving on-board cameras due to unpredictable environmental variables. Specifically, an effective TSDR system must simultaneously overcome dynamic lighting conditions such as severe glare or adverse weather, motion blur and distortion induced by high driving speeds, and the physical degradation or partial occlusion of signs in the realworld. Furthermore, processing continuous video feeds requires substantial computational power, creating a pressingneedforanoptimized,DeepLearning-basedsoftwaresolution. ByleveragingConvolutionalNeuralNetworks(CNNs),thisprojectaimstodevelopalightweightmodelcapableofinstantaneousspatialfeature extractionandreal-timeinferenceonstandardvehicularhardware,therebyovercomingtheseenvironmental challenges to bridge the gap between theoretical accuracy and practical, safe autonomous navigation.

IV. IMPLEMENTATION

The Traffic Sign Detection and Classification system is developed using Python, integrating OpenCV, NumPy, and machine learning models such as SVM/CNN. The implementation is carried out in the following phases:

1) *Data Acquisition:*
Traffic sign images are collected from a dataset and video input is taken using a webcam or video file for real-time processing.

2) *Preprocessing:*
TheinputframesareresizedandconvertedintograyscaleorHSVcolorspace.Noiseisreducedusingfilters, and contrast enhancement techniques are applied to improve visibility.

3) *SegmentationandDetection:*
Colorbasedsegmentationisusedtoisolatetrafficsigncolors(red,blue,etc.).Edgedetection(e.g.,Canny)andcontourdetectionmethodsareappliedtoidentifycandidateregions.Shapedetectiontechniqueshelpin filtering circular or triangular signs.

4) *ROIExtractionand Normalization:*
Thedetectedregionsarecroppedandresizedtoafixeddimensiontomaintainconsistencybeforeclassification.

5) *Feature Extraction:*
Featuressuchas Histogramof OrientedGradients(HOG)or pixel-basedfeatures are extracted torepresent the image numerically.

6) *ModelTrainingand Classification:*
A machine learning model (SVM or CNN) is trained using labeled data. During execution, the extractedfeatures are passed to the trained model to predict the class of the traffic sign.

7) *Real-TimeRecognition:*
Thesystemprocesseseachframecontinuouslyandperformsdetectionandclassificationinreal time.

8) *OutputVisualization:*
Detected traffic signs arehighlighted using bounding boxes, and corresponding labels are displayedon the screen.

9) *SystemIntegration:*
All modules are integrated into a single pipeline to ensure smooth execution from input capture to output display.

V. RESULT

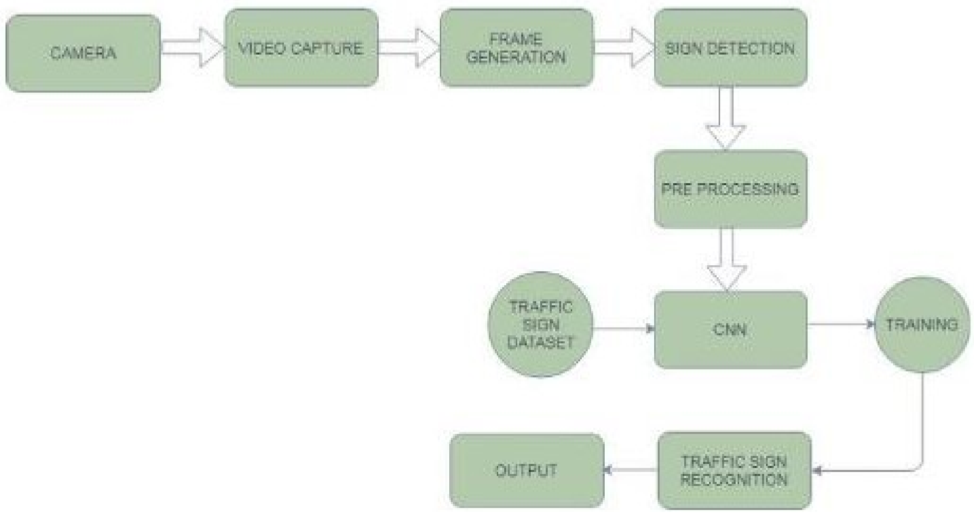
International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

VI. METHODOLOGY

ThebasicsimplearchitectureoftheTSDRsystemconsistsoftwomainstages.Thefirststageisthedetectionstagewhichtakestheinputimageorvideotoidentifythetrafficsignfromthecapturedimage.Thecapturedimageispassedasaninputinthedetectionphasewherethenoiseorunwantedbackgroundfromthecaptured image is removed. In the second stage i.e Recognition phase the image generated from the last phase is compared and identified from the existing database to uniquely recognize the traffic sign. This recognition phase uses several features of the traffic sign such as color, shape, size, texture, etc. to extract the sign information.

A. SoftwareStructureandProposed System

The software is developed by installing the following packages on the phyton environment respectively; OpenCV, NumPy, Keras, Pandas, Scikit-learn, Scikit-image, Matplotlib, Battery, TensorFlow for CPU and GPU.After theinstallation of thesepackages, the Phytonprogramming environment is created completely. GPU-based encodings accelerate the learning time and reduce the computational cost. The flowchart of the proposed study is illustrated.



EDA: This is a preprocessing technique in which the image processing techniques are applied to the image data to enhance the accuracy of the model.

*Dataaugmentation*isatechniquethatcansignificantlyincreasethedatainstancesofadatasettotrainamodel. In the case of image datasets, the technique uses the basic image processing operations, such as flipping, rotating, cropping, padding, zoom, shear, etc. for augmentation. The dataset is then extended by these transformed images resulted from the existing image set, which increases the size of the dataset to train the neural networks. To solve the problem of the availability of a small size dataset that was affecting the performance of the proposed CNN, the data augmentation method has been used in this study. This provides more learning features to the learning model.

*ModelTraining:*Inthisstep,wewillbuildanarchitectureoftheCNNmodelusingKeras,TensorFlowlibraries and train the training dataset using the model built.

VII. FUTURE SCOPE

1) Real-Time Implementation in Vehicles

In the future, this system can be directly integrated into vehicles as part of Advanced Driver Assistance Systems (ADAS). It will continuously detect traffic signs using onboard cameras and provide real-time alerts to drivers. This can help in reducing accidents caused by missed or unnoticed traffic signs and improve overall road safety.

2) Mobile Application Development

The system can be converted into a mobile application that uses a smartphone camera to detect traffic signs. This would make the technology more accessible to common users. Drivers can use their phones as a low-cost alternative to expensive in-vehicle systems, especially in developing countries.

3) Improved Accuracy with Advanced Deep Learning Models

Future improvements can include the use of more advanced deep learning techniques such as YOLO (You Only Look Once), ResNet, or Transformer-based models. These models can provide faster and more accurate detection, even in complex environments with multiple signs or background noise.

4) Detection in Extreme Environmental Conditions

Currently, systems may struggle in conditions like rain, fog, night-time, or poor lighting. Future work can focus on improving image processing techniques and training the model on diverse datasets so that it performs reliably under all weather and lighting conditions.

5) Multi-Language Support

Traffic signs in different regions may include text in various languages. The system can be enhanced using Optical Character Recognition (OCR) to read and translate text on signs. This will help drivers understand signs even in unfamiliar regions or countries.

6) Integration with Autonomous Vehicles

Traffic sign recognition is a key component of self-driving cars. In the future, this system can be integrated with autonomous vehicle technology to help vehicles make decisions such as stopping, slowing down, or changing lanes automatically based on detected signs.

VIII. CONCLUSION

The primary objective of this paper is to comprehensively analyze the developmental trajectory and key advancements within the field of Automatic Traffic Sign Detection and Recognition (TSDR). To contextualize the current state of the art, this study provides an extensive summary of recent research, explicitly highlighting the persistent environmental issues and operational challenges that complicate the detection process. Conditions such as adverse weather, variable illumination, motion blur, and complete darkness not only impair the visual acuity of human drivers but also severely degrade the performance of optical sensors. By detailing these vulnerabilities, this paper underscores the critical necessity for highly robust and adaptable recognition systems in modern autonomous vehicles.

Historically, the detection and classification of traffic signs have relied heavily on hand-crafted feature extraction. This study delves into these traditional methodologies, examining how early systems utilized distinct visual characteristics—such as standardized geometric shapes, high-contrast color palettes, and specific textural patterns—to isolate signs from complex background clutter. Furthermore, we explore a variety of conventional and hybrid object detection frameworks, analyzing how these algorithms integrate multiple feature sets to identify objects within dynamic environments. While these foundational methods provided early success, their reliance on rigid, predefined rules often limits their effectiveness in unpredictable, real-world driving conditions.

To transcend the limitations of manual feature engineering, this project formally adopts a Convolutional NeuralNetwork(CNN) architecture.CNNshaveunequivocallyemergedas theoptimal and most dominant solution for complex computer vision applications. Compared to traditional machine learning networks, CNNs stand vastly superior in terms of classification accuracy, computational efficiency, and ease of implementation. The most significant advantage of deploying a CNN is its capacity for hierarchical, autonomous feature extraction. Unlike predecessor algorithms that require tedious human supervision to define visual rules, a CNN inherently learns without explicit programming. In our implementation, the network was fed a highly diverse dataset comprising thousands of traffic sign images. Through iterative training,thedeeplearningalgorithm autonomously learnedtoidentifythemostsalientanddistinctivespatial features for each specific traffic sign class, ultimately achieving high accuracy and robust real-time performance.

REFERENCES

[1] Traffic sign detection and recognition based on convolutional neural networks by Md Tarequl Islam Department of Electrical and Electronics Engineering Student of Engineering, Ahsanullah University of Science and Technology. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol.2. Oxford: Clarendon, 1892, pp.68–73.

[2] Research on Traffic Sign Detection Based on Convolutional Neural Network by Zhonghu Wang East China University of Science and Technology Shanghai China K. Elissa, "Title of paper if known," unpublished.

[3] MogelmoseA,TrivediMM,andMoeslundTB.“VisionBasedTrafficSignDetectionandAnalysisforIntelligentDriverAssistanceSystems:PerspectivesandSurvey”,TransactionsonIntelligentTransportation Systems, pp. 1484-1497, (2012), DOI:10.1109/TITS.2012.2209421.

[4] Wali SB, Hannan MA, Hussain A, and Samad SA. “Comparative Survey on TrafRecognition: A Review”, PrzegladElektrotech, pp. 38-42, (2015), DOI:10.15199/48.2015.12.08.

[5] SermanetPandLeCunY.“Trafficsignrecognitionwithmultiscaleconvolutionalnetworks”,inNeuralNetworks(IJCNN),TheInternationalJointConference,IEEEXplore,DOI:10.1109/IJCNN.2011.6033589.pp.2809-2813,(2011),

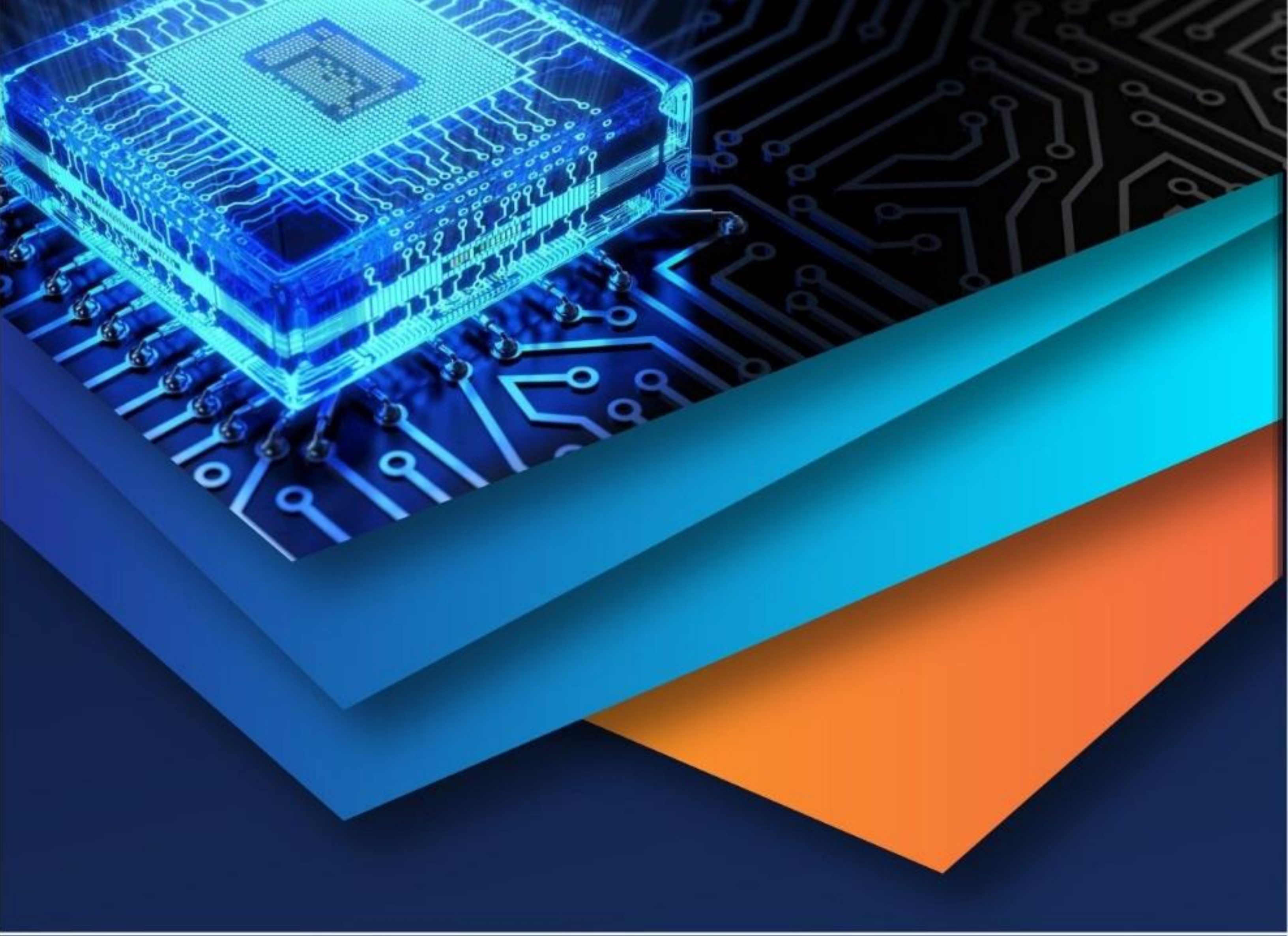
[6] JarrettK,KavukcuogluK,RanzatoM,andLeCunY.“Whatisthebestmultistagearchitectureforobject recognition?”, Computer Vision, IEEE Xplore 12th International Conference, DOI:10.1109/ICCV.2009.5459469. pp. 2146- 2153, (2009),

[7] Ciresan D, Meier U, Masci J, and Schmidhuber J. “A committee of neural networks for traffic sign classification” IEEE Xplore International Joint Conference on Neural Networks-IJCNN, pp. 1918-1921, (2011), DOI:10.1109/IJCNN.2011.6033458.

[8] Krizhevsky A, Sutskever I and Hinton GE. “ImageNet classification with deep convolutional neural networks”, NIPS, pp. 1106-1114, (2012), DOI:10.1145/3065386

[9] BelaroussiR,FoucherP,TarelJP,SoheilianB,CharbonnierPandPaparoditisN.“RoadSignDetection in Images, A Case Study”, 20th International Conference on Pattern Recognition (ICPR), pp. 484-488, (2010), DOI:10.1109/ICPR.2010.1125.

[10] S. Lyu and E. P. Simoncelli, “Nonlinear image representation using divisive normalization” pp. 1-2, (2008), DOI:10.1109/CVPR.2008.4587821.



crossref
10.22214/IJRASET

INDEX COPERNICUS
45.98

ISRA JIF
IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY