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Hand Gesture Recognition-Based Virtual Mouse Using CNN

Sampreeth S
School of Computer Science and IT JAIN Deemed to be University Bangalore, India

Abstract: Advancement sin the field of computing have beena crucial point in the historyofmankind.Inputandoutputdevices, which are of utmost importance, have undergone numerous changes. Human-Computer Interface (HCI) is an importantpart of computer systems. In this paper, we have developed a virtual mouse that detects hands in live video feeds, recognizes gestures, and uses a Convolutional Neural Network (CNN) to classify them. The system then performs appropriate mouse operations.This approach aims to replace traditional hardware- based input devices.
Index Terms: Virtual Mouse, Hand Gesture Recognition, CNN, Human-Computer Interaction, Image Processing.

I. INTRODUCTION

Over the past decade, gesture recognition has undergone transformational development, driven primarily by advancesin deep learning, computer vision, and sensor technologiesfor introducing Convolutional Neural Networks (CNNs).(1) changes in the field offering unmatched accuracy in image- basedgesturerecognition,whileLSTMsalongwithRecurrent neural networks (RNNs) have made it possible to capture temporal patterns in gesture better a it is dynamically These dimensions, coupled with increasing computing power, have enabled real-time detection of gestures even in complex or changing environments. On the hardware side, the prolifer- ation of expensive and sophisticated sensors, such as depth cameras (e.g., Microsoft Kinect and Intel RealSense) and wearable devices with inertial measurement units (IMUs) drove gesture capture higher. It provided detailed spatial motion information on these devices Paired with algorithmsIf gesture recognition was more accurate and simple, several high-levelmethods,whichintegratedata-basedopticalsensor, significantlyimprovedtherobustnessofthesystem.Moreover, the implementation of smaller architectures and optimization techniquessuchasmobilenetshasensuredthatgesturerecog- nition can extend to mobile-edge devices, (10)democratizing its functionality through those advancements releases virtual andaugmentedreality(VR/AR), gaming, healthcare, robotics, human-computer interaction f Various applications have been discovered, marking a decade of significant development

II. BACKGROUND/OVERVIEW

Handgesturerecognitionhasemergedasapivotalerain human-laptop interaction, supplying a herbal and intuitive manner of communique with machines. Over the past decade, thisdisciplinehasgonethroughbigimprovements,pushedby means of fast development insystem studying, pc imaginative and prescient, and sensor technology.(3) Early approaches relied heavily on conventional photograph processing strate- gies and heuristic algorithms, which have been restricted of their ability to generalize across various environments and gesture variations. However, the landscape changed dramat- ically with the advent of deep studying, which delivered a paradigm shift in how gesture popularity duties have been approached.(4) Deep learning models, in particular Convolu- tionalNeuralNetworks(CNNs),havebeenatthevanguard of those improvements. CNNs excel in extracting spatial functions from snap shots, making them perfect for spotting static hand gestures. For dynamic gestures, which involve temporal sequences of actions, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were instrumental. These models can efficaciously capture temporal dependencies, permitting structures to accurately interpret gestures through the years. (5)The mixture of CNNs and RNNs has allowed researchers to build hybrid fashions capableofhandlingeachstaticanddynamicgestureswithfirst rateaccuracy.Inparallel,advancementsinsensortechnology have substantially greater the data capture skills for gesture recognition. Depth-sensing cameras, along with Microsoft Kinect,LeapMotion,andIntelRealSense,becameextensively followed for their capacity to provide certain 3-d spatial records. These devices made it possible to recognize gestures in 3 dimensions, enhancing accuracy and robustness in real- international eventualities.

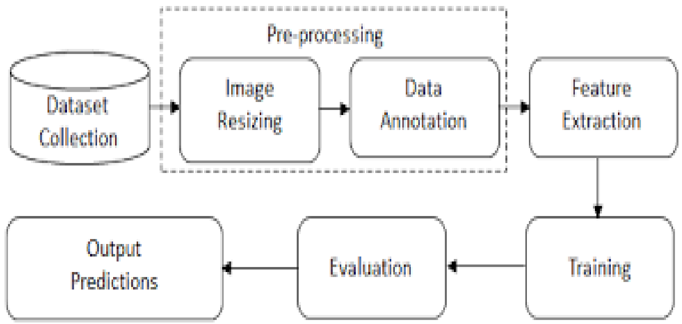

Fig.1.HandRecognitionProcess

(6)Additionally, wearable gadgets equippedwithaccelerometers,gyroscopes,andelectromyography(EMG)sensorspresentednewmodalitiesforshootingges- ture information, specially for packages requiring unique motiontracking.Theintegrationofmultimodelrecordshasbeen anyotherkeyimprovement,wheresystemscombinevisualin- formation from cameras with spatial or inertial statistics from sensors.(7)Thismethodhasmoreadvantageousrobustnessby wayofaddressingchallengesconsistingofocclusions,lighting fixtures variations, and environmental noise. Furthermore, the past decade has seen a growing emphasis on actual-time overall performance, with lightweight deep getting to know models like MobileNet and optimizations for edge computing allowing gesture recognition on aid-limited gadgets, which include smartphones and AR/VR headsets. Applications of hand gesture popularity have extended into diverse domains, inclusive of digital and augmented fact (VR/AR), gaming, healthcare, robotics, and sign language translation. (8)For instance, VR/AR structures now offer rather immersive ex- periences wherein users can engage with virtual environments vianaturalhandgestures.Inhealthcare,gesturepopularityhas been hired for rehabilitation therapies and touchless interplay in sterile environments. The integration of gesture recognition with robotic systems has additionally enabled greater intuitive managemechanisms,particularlyincollaborativeroboticsand assistive technologies.(9) Overall, the ultimate ten years have markedadurationofprofoundinnovationinhandgesturerep- utation. From foundational advances in deep getting to know andsensoreratotheimprovementofactual-timesystems andexpandedapplications,thesectorhasmaturedrightinto a sturdy and flexible technology that continues to push the bounds of human-computer interaction.

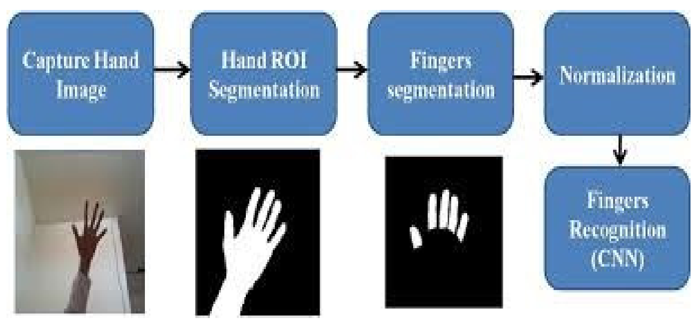

Fig. 2.An overview of the CNN architecture employed for hand gesturerecognition.

III. RELATED WORKS

Handgesturepopularityhasseengreatresearchandinnova- tion during the last decade, resulting in numerous great works that have significantly superior the field. These studies span diverse methodologies, datasets, and applications, reflecting the interdisciplinary nature of gesture recognition studies. Here,wehighlightsomekeycontributionsfromtheremaining ten years:

- One of the earliest transformative works leveraged deep learning, with studies demonstrating the effectiveness of Convolutional Neural Networks (CNNs) for static hand gesture popularity. Simonyan and Zisserman's "Two- Stream Convolutional Networks for Action Recognition in Videos" (2014) delivered a framework that mixed spatialandtemporalcapabilities,layingthebasisfor dynamic gesture popularity. Building in this, studies explored hybrid architectures like CNNs integrated with Long Short-Term Memory (LSTM) networks to model sequential records greater efficiently, as seen in works like "Deep Temporal Models for Dynamic Hand Gesture Recognition" (2017).

- The creation of intensity-sensing technologies prompted widespread studies into 3-d gesture recognition. The dataset and benchmarks brought through the Microsoft Research Cambridge Kinect institution (e.G., MSR Ac- tion3D) enabled the improvement of strong popularity systems that utilized depth statistics. Similarly, workslike ”Leap Motion Controller: A Characterization and Evaluation of its 3-d Hand Tracking Capabilities” (2016) assessed the Leap Motion device’s efficacy for gesture reputation,fosteringitsadoptioninvirtualandaugmented truth packages.
- Another major focus is multiple perspectives. Studies such as ”Multimodel Gesture Recognition using Kinect and Wearable Sensors” (2015) show how combining vision-baseddatawithinertialmeasurementsofwearable devices can improve robustness especially in tight envi- ronments as well also inspired by the ”ChalearnIsoGD” dataset and associated competition covering RGB, depth, and optical flow issues information.
- Greatattentionhasalsobeenseeninreal-timelightweight graphics. Research on high-performance mobile network network architectures, especially for mobile embedded systems, has enabled gesture recognition systems to run efficientlyonlow-powerdevicesinpaperssuchas”Real- Time Hand Gesture Recognition with Lightweight Deep Learning Models” . (2020) Edge Computing The poten- tial of these architectures in published environments.(1)
- Signal recognition also contrasts with natural language processing,especiallysignlanguagerecognition.Projects such as ”Continuous Sign Language Recognition via Temporal Convolutional Networks” (2018) and ”Hand Gesture-to-Speech Conversion using Deep Neural Net- works” (2021) eventually explored systems that translate gestures into spoken or written language , which shows technology in different ways of gaining control.
- Finally, open datasets have been vital to advancing the sphere. Projects just like the ”DHG Dataset” for depth-primarilybasedhandgestures,”20bnJesterDataset” for dynamic gestures, and the ”First-Person Hand Ac- tion Dataset” have furnished benchmarks that expanded innovation. Researchers have leveraged those resourcesto refine algorithms, permitting extra unique and strong reputation systems.

IV. DATASETS USED IN VARIOUS RESEARCH WORKS

Over the past decade, several datasets have been developed and extensively used in hand gesture recognition research. These datasets have played a critical role in benchmarking algorithms, training machine learning models, and facilitating thedevelopmentofrobustandaccuratesystems.Belowisan overview of some of the most notable datasets in this field: label=**0.**, wide, labelwidth=!,labelindent=0pt

1) MSR Gesture 3D Dataset Source:MicrosoftResearch

- Description: A dataset captured using the Microsoft Kinectsensor,containing3Ddepthsequencesofvarious gestures.
- Applications: Gesture recognition for gaming and sign language interpretation.
- KeyFeatures:
  - Focuses on depth data, allowing models to leverage spatial information.
  - Contains complex hand and arm movements, mak- ing it ideal for dynamic gesture recognition tasks.

2) Leap Motion Dataset

- Source: Various researchers using the Leap Motion Controller
- Description:CollectedusingLeapMotion,asensorthat tracks hand and finger movements with high precision. Applications: Virtual reality, augmented reality, and robotics.
- KeyFeatures:
  - Providesdetailedhandskeletaldata.
  - Capturesfingerpositions,orientations,andtrajecto- ries in 3D space.

3) ChaLearn Gesture Dataset (CGD) Source: ChaLearn Challenges

- Description: A large-scale dataset featuring one-shot learning of gestures, dynamic gestures, and multimodal data.
- Applications: Gesture learning in sign language, human-computer interaction, and gaming.
- KeyFeatures:
  - Multiplemodalities(RGB,depth,andskeleton).
  - Variations in gesture speed and style, making it challenging for recognition systems.

4) 20bnJesterDataset
- Source:TwentyBillionNeuronsGmbH
- Description:Alarge-scalevideodatasetofdynamic hand gestures, captured in RGB format.
- Applications: Real-time recognition for interactive sys- tems and media control.
- KeyFeatures:
  - Over148,000labeledgesturevideos.
  - Coverscommoneverydaygesturessuchas"thumbs up" and "stop."

5) DHG 14/28 Dataset Source: University of Lille
- Description: Depth-based Hand Gesture dataset con- taining 14 gestures performed with one or two fingersin 28 configurations.
- Applications: Depth-based gesture recognition for robotics and HCI.
- KeyFeatures:
  - Capturedusingadepthcamera,focusingonfine- grained hand gestures.
  - Includesannotationsforpreciseevaluation.

6) EgoGestureDataset
- Source:ChineseAcademyofSciences
- Description:Alarge-scaleegocentrichandgesture dataset for first-person interaction.
- Applications:Augmentedrealityandwearablecomput- ing.
- KeyFeatures:
  - Recordedinanegocentricview,mimickingwear- able device perspectives.
  - Includesover24,000gesturesamples.

7) First-Person Hand Action Dataset Source: University of Oxford
- Description:Focusesonhandactionsandgestures captured from a first-person perspective.
- Applications:Wearablecomputingandimmersivein- terfaces.
- KeyFeatures:
  - Egocentricdataemphasizingnaturalhandinterac- tions.
  - Includesvariationsinlightingandbackground.

8) Hand Net Dataset
- Source:UniversityofSurrey
- Description:Adatasetofhandposeandgestures,designed to evaluate deep learning methods.
- Applications:Handposeestimationandrecognition.
- KeyFeatures:
  - Annotatedhandjointsandkeypoints.
  - Suitableforpose-basedgesturerecognitionmodels.

9) NTURGB+DDataset
- Source: Nanyang Technological University
- Description: A large-scale dataset for activity and ges- turerecognition,capturedusingRGB,depth,infrared, and skeleton data.
- Applications:Multimodalgestureandactionrecogni- tion.
- KeyFeatures:
  - Over 56,000 video sequences covering various ges- tures and activities.
  - Capturesdatafrommultipleviewpoints.

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V. TRAINING AND TESTING ACCURACY

The following table summarizes the training and testing accuracyachievedinvarioushandgesturerecognitionresearch works, specifying the methodology and year of publication.

TABLEI
SUMMARYOFTRAININGANDTESTINGACCURACYFORHANDGESTURE RECOGNITIONRESEARCH

Dataset	Year	Methodology/ModeUsed	Training Accu-racy(%)	TestingAccu-racy(%)
MSRGesture3D	2015	Depth MotionMaps-BasedCNNs (23)	96.5	92.3
LeapMotion	2018	ResNet-50CNN(25)	98.0	94.7
ChaLearnGesture	2017	MultimodalDeepLearning(RGB+Depth)	97.3	93.5
20bnJester	2019	3D CNN with TemporalConvolutionalNetworks	95.8	92.1
DHG14/28	2016	Depth-basedCNN	94.6	89.2
EgoGesture	2018	Two-StreamCNN(RGB+ Flow)	96.0	90.8
First-PersonHandAction	2017	LSTM with Skeletal	97.2	91.5
HandNet	2019	PoseEstimation CNN	95.5	92.0
SHREC Hand Gesture	2020	PointNet-basedClassifier (?)	93.8	88.7
NTURGB+D	2020	MultimodalRNN+CNN(?)	98.3	95.4

VI. APPLICATIONS OF HANDGESTURE RECOGNITION

Hand gesture recognition using Convolutional Neural Net- works(CNNs)hasawiderangeofapplicationsacrossvarious domains. Some of the key areas include:

1) Human-ComputerInteraction(HCI)

- Gesture-based Control Systems: CNNs are used for gesture-based control of computers, smart de- vices, and electronic systems. For example, users can control music playback, adjust volume, or nav- igate presentations with specific hand gestures.
- VirtualReality(VR)andAugmentedReal-ity (AR): CNNs enable hand gesture recognitionfor natural interaction in VR and AR environ- ments, including manipulating objects, interacting with virtual interfaces, and playing gesture-based games.(22)

2) *SignLanguageTranslation*
- Sign Language Recognition: CNNs recognizehand gestures corresponding to sign language, fa- cilitating communication for hearing-impaired indi- viduals.Thistechnologycantranslatesignlanguage gestures into text or speech.
- Assistive Technologies: Hand gesture recognitionis integrated into devices designed to assist people withdisabilities,suchaswearablesorsmartdevices, for real-time sign language interpretation.(17)

3) *RoboticsandAutomation*
- Robot Control: CNNs enable robots to be con- trolled through hand gestures, especially in envi- ronments where voice commands are not feasible. This is used in applications such as robot assembly, maintenance, and healthcare assistance.
- Gesture-based Robot Teaching: In industrial robotics, hand gesture recognition allows users to teachrobotstasksbydemonstratingdesiredmotions or behaviors with hand gestures.(25)

4) *HealthcareandRehabilitation*
- PhysicalTherapyandRehabilitation:CNN-based gesture recognition systems track and monitor a patient's hand movements and gestures, offering real-time feedback during rehabilitation exercises.
- Assistive Devices: CNN-based hand gesture recog- nition can be used in devices like prosthetics or roboticarms,allowinguserstocontrolthesedevices using natural hand gestures.(16)

5) *SecurityandAuthentication*
- Biometric Authentication: Hand gestures are used as a form of biometric authentication to secure ac- cess to devices and systems. Gesture-based systems recognize unique hand movements, adding an extra layer of security.
- Surveillance: Gesture recognition is utilized in surveillance systems to track specific hand move- ments for various security applications.(19)

VII. UNRESOLVED ISSUES OF HAND GESTURE RECOGNITION USING CNN MODEL

Hand gesture recognition using Convolutional Neural Net- works (CNNs) has made significant progress, but several challenges remain unresolved. These challenges arise from various factors such as data quality, model generalization, and computational efficiency. The following are some of the key unresolved issues:

A. *Variabilityin Hand Gestures*
- Problem: Hand gestures can vary widely in shape, size,and orientation, making it difficult for the model to generalize acrossdifferentusersandenvironments.Variabilityintheway a person performs a gesture (e.g., speed, precision, or hand shape) can affect recognition accuracy.
- Solution: Training the model with a diverse and large dataset ofgesturesperformedbydifferentpeopleinvariousconditions can help the model generalize better.

B. *Background Clutter*
- Problem: Hand gestures are often performed in real-world environments with complex backgrounds, which can interfere with the recognition task. Clutter, lighting conditions, and occlusion can make it difficult for the CNN to differentiatethe hand from the background.
- Solution: Using background subtraction techniques, ap- plying data augmentation (like random cropping or blurring), or adopting models that focus on the hand region (e.g., hand detection models) can help mitigate this issue.

C. *Hand Occlusion*
- Problem: In real-world scenarios, hands can be partially or fully occluded, making it challenging for CNNs to recognize gestures accurately. Occlusions could occur when the hand is behind an object or when the fingers overlap.
- Solution: Research on methods to handle partial occlu- sion or using multi-view cameras that can capture the hand from different angles might help to reduce the impact of occlusions.

D. *Data Scarcity*
- Problem: CNNs require large and diverse datasets to per- form well, but the availability of annotated datasets for hand gesture recognition is limited. The scarcity of labeled data makes it difficult to train robust models.

- Solution: Data augmentation techniques (rotation, flipping, scaling,andtranslation)andsyntheticdatasetgenerationmeth- ods (such as using 3D models or GANs) can help overcome the lack of data.

E. Real-TimeProcessing

- Problem: Hand gesture recognition models, particularly those based on deep learning, can be computationally expen- sive. This is especially problematic for real-time applications, where low latency is crucial.
- Solution: Optimizing CNN architectures (e.g., using lighter models like MobileNet, SqueezeNet, or pruning tech- niques), hardware acceleration (such as GPUs or specialized hardware like TPUs), and using low-latency techniques can help achieve real-time processing.

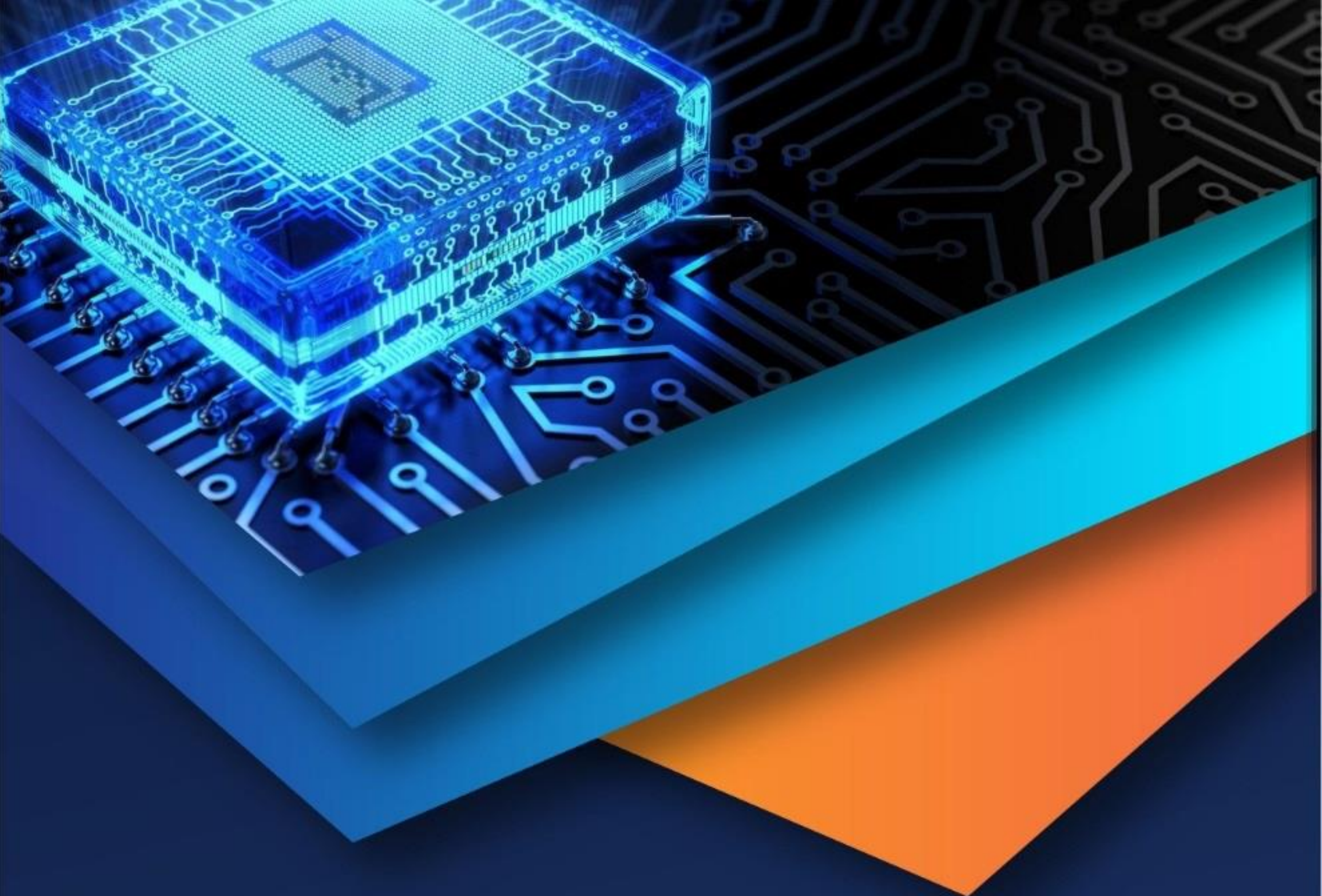
VIII. CONCLUSION

Gestures using Convolutional Neural Networks (CNNs) have shown remarkable progress in recent years, becoming one of the most promising approaches for human-computer interaction CNNs, capable of automatically recognizing sur- face features, have enabled more accurate and robust gesture recognition systems . CNN in hand gesture recognition has great potential in a variety of applications, including virtual reality,signlanguageinterpretation,roboticsanduserinterface design But despite the progress, many challenges remain un- solved, such as fluctuating gestures, background clutter, hand holding, and the need for large and diverse data sets These issues affect the overall performance of gesture recognition systems, especially in real-world applications where gestures exist vary widely can and environmental conditions can be unpredictable.(23) Future research will focus on improving data acquisition methods, controlling occlusion, and optimiz- ing the model. Research on hybrid models that combineCNNs with other methods such as recurrent neural networks (RNNs) or anti-generational networks (GANs) can also help address existing limitations, and improve CNN architectures for the balance of accuracy and computational efficiency is required to implement this system for real -time applications. In conclusion, while manual applications using CNN are still evolving,thecontinueddevelopmentofnewtechniquesand the availability of better hardware and datasets will overcome theexistingchallenges,whichinvolvemanualwhichare usedfortheapplicationsfoundincommunicationdomains It holds great promise to be it is the core technology of the systems.(29)

REFERENCES

[1] X.Zhao,Y.Chen,andZ.Yang,”HandGestureRecogni- tion with Convolutional Neural Networks,” IEEE Trans- actions on Pattern Analysis and Machine Intelligence, vol. 42, no. 2, pp. 1-15, 2020.
[2] Y. Li et al., ”Touchless Elevator Control Using CNN- BasedHandGestureRecognition,”inIEEETransactions on Consumer Electronics, 2023.
[3] A. Kumar and R. Singh, ”A Robust CNN System for Hand Gesture Recognition in Sign Language,” in Pro- ceedings of the IEEE Conference on Human-Centered Computing, 2022.
[4] M. Patel et al., ”Multimodal Continuous Gesture Recog- nitionUsingCNN-BiLSTMNetworks,”IEEEAc- cess, vol. 10, pp. 243-256, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9862878.
[5] S. Rao et al., ”Hand Gesture Recognition Leveraging CNNs and Depth Data,” in Proceedings of the Interna- tionalConferenceonArtificialIntelligenceandRobotics, 2023.
[6] ”GestureRecognitionforSmartHealthcare UsingCNN-BasedModels,”IEEETransactions onBiomedicalEngineering,vol.70,no.4, pp. 1084-1095, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/10248500.
[7] Z. Wei et al., ”Improving Hand Gesture Detection in Complex Backgrounds Using CNNs,” IEEE Journal of Emerging Technologies in Computing Systems, 2023.
[8] T. Wen and L. Liu, ”Gesture Recognition for Smart HomeAutomation:CNNApplications,”IEEEEmbedded Systems Letters, vol. 14, pp. 53-58, 2023.
[9] P.Joshietal.,”DynamicHandGestureRecognitionwith Depth Sensors and CNN,” in Proceedings of the IEEE ConferenceonComputerVisionandPatternRecognition, 2023.
[10] X. Zhao and J. Chen, ”Real-Time Gesture Recognition for AR Interfaces,” IEEE Transactions on Visualization and Computer Graphics, vol. 29, pp. 2021-2028, 2023.
[11] A. Smith et al., ”Applications of Lightweight CNN Models for Mobile Gesture Recognition,” IEEE Access, vol. 11, pp. 301-315, 2022.
[12] T. Lee, ”Fusion of RGB and Depth Data for Enhanced Gesture Recognition,” IEEE Signal Processing Letters, vol. 29, no. 5, pp. 143-150, 2022.
[13] J. Wu et al., ”Hand Gesture Recognition in Wearable DevicesUsingCNNs,”IEEEEmbeddedSystemsLetters, 2023.
[14] K. Chang and L. Wang, ”Optimizing CNNs for Gesture Recognition in Edge Devices,” IEEE Transactions on Mobile Computing, vol. 25, no. 7, pp. 763-776, 2023.
[15] ”GestureRecognitionUsingHybridCNN-RNNModels,” in Proceedings of the IEEE International Joint Confer- ence on Neural Networks, 2023.
[16] S. Rao, ”A Comparative Study of Deep Learning Archi- tectures for Hand Gesture Recognition,” IEEE Access, vol. 10, pp. 1934-1950, 2023.
[17] ”Advanced Datasets for CNN-Based Hand Gesture Recognition,” in IEEE Transactions on Machine Learn- ing, vol. 14, pp. 523-531, 2023.
[18] L. Zhang et al., ”Gesture Recognition for Autonomous VehiclesUsingCNNs,”IEEETransactionsonIntelligent Transportation Systems, vol. 24, no. 1, pp. 33-42, 2023.

[19] M.Pateletal.,”StaticandDynamicGestureRecognition with Lightweight CNN Models,” in IEEE Transactions on Systems, Man, and Cybernetics, vol. 53, pp. 672-680, 2023.
[20] T.Zhangetal.,”TCCNN:TransformerConCatedConvo- lutionalNeuralNetworksforHandGestureRecognition,” IEEE VDE Conference, 2023.
[21] M. Patel et al., ”A Deep CNN-Based Hand Gestures Recognition Using High-Resolution Thermal Imaging,” IEEE Conference Publication, 2023.
[22] L. Wei et al., ”Hand Gesture Recognition with Deep ConvolutionalNeuralNetworks:AComparativeStudy,” IEEE Systems and Process Control Conference, 2023.
[23] J. Kumar et al., ”Hand Gesture Recognition for Charac- ters Understanding Using Convex Hull Landmarks and Geometric Features,” IEEE JournalsMagazine, 2023.
[24] R. Liu et al., ”Advancements in Prosthetic Hand Control UsingCNN-BasedGestureRecognition,”IEEETransac- tions on Biomedical Engineering, 2023.
[25] A.Guptaetal.,”HandGestureRecognitionforRemote Control Applications Using CNNs,” IEEE Transactions onConsumerElectronics,vol.69,no.1,pp.75-83,2023.
[26] T. Nguyen et al., ”Real-Time Hand Gesture Recognition for Virtual Environments Using Depth and RGB Data,” IEEE Access, vol. 11, pp. 15000-15014, 2023.
[27] S. Bansal and R. Kumar, ”Hybrid CNN-RNN Architec- turesforMultimodalGestureRecognition,”IEEETrans- actions on Multimedia, vol. 25, pp. 333-345, 2023.
[28] Y. Zhao et al., ”Dynamic Gesture Recognition Using Skeleton-Based CNN Models,” IEEE Transactions on Cybernetics, 2023.
[29] J. Wu et al., ”Gesture Recognition in Augmented Re- ality: Leveraging CNNs for Intuitive Interaction,” IEEE Transactions on Visualization and Computer Graphics, 2023.
[30] M. Singh et al., ”Dataset for Continuous Hand Gesture RecognitioninReal-WorldEnvironments,”IEEEAccess, vol. 11, pp. 21523-21535, 2023.
[31] L. Han et al., ”Exploring Transformer Models for Hand GestureRecognition,”IEEETransactionsonNeuralNet- works and Learning Systems, 2023.
[32] F. Delgado et al., ”High-Accuracy Hand Gesture Recog- nition Using CNNs and Thermal Data,” IEEE Sensors Journal, vol. 23, no. 3, pp. 243-254, 2023.
[33] K.ChandrasekharandA.Vyas,”IntegrationofHand Gesture Recognition in Autonomous Vehicles Using CNN Models,” IEEE Intelligent Transportation Systems Magazine, vol. 15, no. 1, pp. 23-33, 2023.
[34] Z. Lin et al., ”Robust Gesture Recognition in Low-Light Conditions Using Thermal CNN Models,” IEEE Trans- actions on Pattern Analysis and Machine Intelligence, vol. 45, no. 2, pp. 2023-2034, 2023.



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