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Advancements and Future Directions in Human Activity Recognition

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Abstract: ***Activity recognition deals with the automation of recognizing various activities by identifying the subject and its interactions with the environment. Human activity recognition deals with identifying different activities like sitting, walking, laying moving, running, jogging, various hand movements, posture and behavior prediction and recognition. Activity recognition deals with the automation of recognizing various activities by identifying the subject and its interactions with the environment. The wide variety of environments are incorporated with Human Activity Recognition. It assists with the vast variety of problems related to people, living, lifestyle, security, monitoring, which may or may not be related to computer science.***
Keywords: Machine Learning, Activity Recognition, Prediction, Human Activity, Deep Learning, Sensors.

I. INTRODUCTION

Various applications are introduced to deploy automation in smart environments , works as important motivating factor for following day to day and in critical activity recognition.

Health Care - In these applications, activity recognition support fitness and critical care. These are implemented via sensors and images and videos concerned to the health care support system.

Security-Through surveillance, prediction and decision support system is benefited to improve the accuracy and classification score. Human activity recognition is implemented in many applications which are related to theft and abnormal human behaviour. But more dataset is required for validation of the models.

Occupancy prediction - By sensors and cameras a load of occupied space and resources are predicted for efficient utilization of resources It is applied for load distribution and prediction and further generation of schedule and smart traffic monitoring and prediction.

Ambient Assisted Living - It supports people for smart lifestyle and lively hood for improving quality of living for smart buildings, city and houses. HAR provides support for scalable and accurate prediction and recognition support systems.

Senior Citizen Monitoring-Senior citizen monitoring is an important application amalgamation with surveillance and monitoring to make senior citizen life independent and safe. These applications improve the quality of life for elderly people which should be safe and secure

Disabled quality life improvement Human Activity Recognition applications focus on disabled person daily activities as hygiene, nutrition and safety. These applications should be implemented in a realistic environment

Monitoring and prediction of activities related to Smart Buildings, offices and cities. Real-time monitoring deals with activity recognition to observe and monitor activity patterns and predict action concerning the sequence of events. These applications provide support to observe the change in behavior and its impact in critical environment

Biologging is the area which deals with tagging for observing animal activity pattern recognition and improve reproductivity of endangered species

II. LITERATURE REVIEW

Human activity Recognition is a new and vast area of research that deals with real-time and frequently changing environments. A variety of learning algorithms (deep learning, self-learning, transfer learning)are implemented to improve prediction accuracy.

Human activity recognition (HAR) plays a very important role in recognizing not only simple human activities such as walking, running, jogging, moving upstairs and downstairs, but also recognizes strange activities performed by a human. Arbitrary and sudden abnormal activities are recognized which are unusual.

Through machine learning, human activities such as walking, running, jogging, moving upstairs and downstairs, etc are recognized through various types of data sets collected from different sensors. Traditional PR module based on decision tree SVM, naïve Bayes, HMM. The limitation of these recognition models is related to the data quality and the need for large training time.

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HAR has been increasingly implemented by deep learning technology. Methods exploit the capability of the classifiers using deep learning, generalized linear model, random forest and ada boost Accuracy of Multi-class SVM is improved by enveloping transition table. Computational time is deflated by eliminating access to Unreachable states .

Accuracy should be improved by using good quality data. More efforts should be required in data collection and preprocessing. Limitations lie in data gathering due to devices limited power and approachability. Mostly wearable sensors and fixed sensors are used in data collection.

Critical data analysis and real-time monitoring of multi-modal dynamic environment credited milestone to feasibility study and risk management for diverse environments. It deals with real-time data processing, which should incorporate dynamic and distributed processing. Parallel processing algorithms support is required for fast and efficient processing.

Existing models should be explored for other applications. Validation of existing algorithm need large dataset can be extended in many ways by improving performances, generalization, analysis, abstraction, and enhancing efficiency. Training time can be reduced by using Hybrid approaches. More scalable and efficient algorithms should be implemented to recognize and predict critical and abnormal behavioral patterns.

Few applications, comparative study and their limitations are described in the following table

Table 1.Comparative study of Related Work

Paper	Advantages	Disadvantages/Limitations	Accuracy
Mai et al[1]	Video Surveillance system for motorbike theft prediction	More work is needed for the prediction of Complex activities. Accuracy should be improved	74.1%
Ka ́ntoch [2]	The proposed prototype is based on a battery-operated wearable health_ monitoring device	Not investigated more features which do not confirm performed activity	82%
Nursultan et al [3]	Random forest is more efficient in recognition is as compare to SVM, and KNN	Training Large dataset by using random forest is time-consuming	84.5%
Mahmood et al [4]	System for adaptive content delivery was developed	The small data set is used	87%
Supriyantgna et al [5]	Home automation &Home Security system is developed	As the distance increases the accuracy of prediction decreases	90.67%
Gao et al [6]	Recognizes various activities efficiently	Accuracy should be improved ..Position of the smartphone may vary	91%
Braganca et al[7]	Low computational cost	Accuracy should be improved	93%
Uddin et al[8]	High-quality features with parallel processing result in high accuracy and low computational cost	More complex activity recognition should be explored, for validation of the proposal large dataset is required	95%
Alawneh et al [9]	Accuracy and training time is improved by incorporating data augmentation	For further validation of the proposal, large data set is required	95%

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Karbala et al [10]	Good Accuracy is maintained concerning limited frame numbers	Improvements in recognition score and prediction time are required	95.3%
Boston et al [11]	Comparative study of machine learning methods to identify better one for recognizing motion activity	Sensor data is processed. optimization and scaling process is required for classification	96%
Alam et al[12]	Computational time is improved, efficiently recognizes IoT datasets with better accuracy	Validation is not done in an extensive way with more diverse	97.1%
Balli et al[13]	Motion Sensor data is processed for recognizing human motion	Not considered hand movements .cooking, eating and smoking.	97.3%
D.Angelo et al.[14]	Inculcating Human Activity recognition for improving the performance of COVID-19 tracking app	Other fields related to fitness and surveillance should also be explored	99.9
Yigitcanlar,et al.[15]	Artificial intelligence Algorithms application for safety of the people through Activity recognition	Data set used for urban areas, more should be required to explore	90%
Palaniappan et.al.[16]	Abnormal Human Activity Recognition	SVM implementation is used . More algorithms should be implemented	98%
Alomari ,Iktishaf et al.[17]	Processing Arabic tweets to Automate road traffic event detection using big data in a distributed environment	In other fields (healthcare and traffic automation) exploration is required	98%
Batty et al.[18]	Application of Artificial Intelligence in smart cities	Urban planning Frame work for smart cities	Theoretical Frame work
Yigitcanlar, Kankanamge, et al[19]	Application of Artificial intelligence concepts in urban planning and development utilization in Australia.	Other perspective should also require to be considered It is a study	92%
Jabanputry et.al[20]	Comparative study of Human activity recognition algorithm	It is a survey	Comparative study

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Ogbuabor et. al[21].	Implementation of Machine Learning algorithms for Human Activity Recognition	Smart phones are used for data collection	95%
Wang et.al.[22]	Hybrid deep learning approach used for Human Activity Recognition	Wearable sensors based data collection	95.8%
Mehmood et. al.[23]	personalised learning with ubiquitous approach is used	Implemented for specific application as teaching Learning . Other applications are required to explore	94%
Htike et.al.[24]	Human Activity Recognition for video surveillance to predict posture	Limited sequence of postures are predicted more data is required to explore more set of posture	96%
Beddiar et.al.[25]	Vision based Human activity recognition is implemented	More data is required for Validation	98%
Arfat et.al [26]	Big data processing for smart infrastructure design opportunities and challenges	Frame work is designed for urban areas	95.6%
Anguita et. al.[27]	Public domain data processing	Smart phones are used for data collection .More data should be explored	90%

III. RECENT CHALLENGES

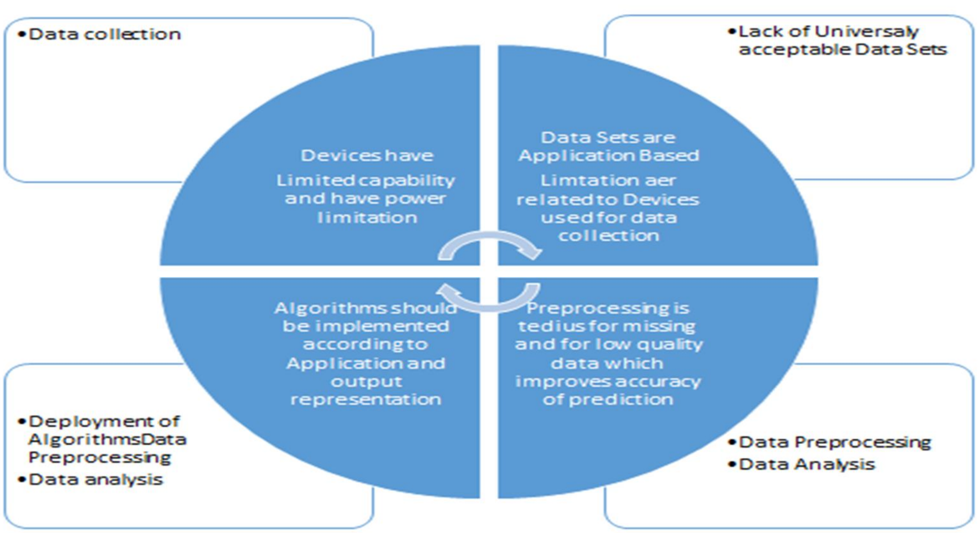

Fig.1. Challenges related to Activity Recognition

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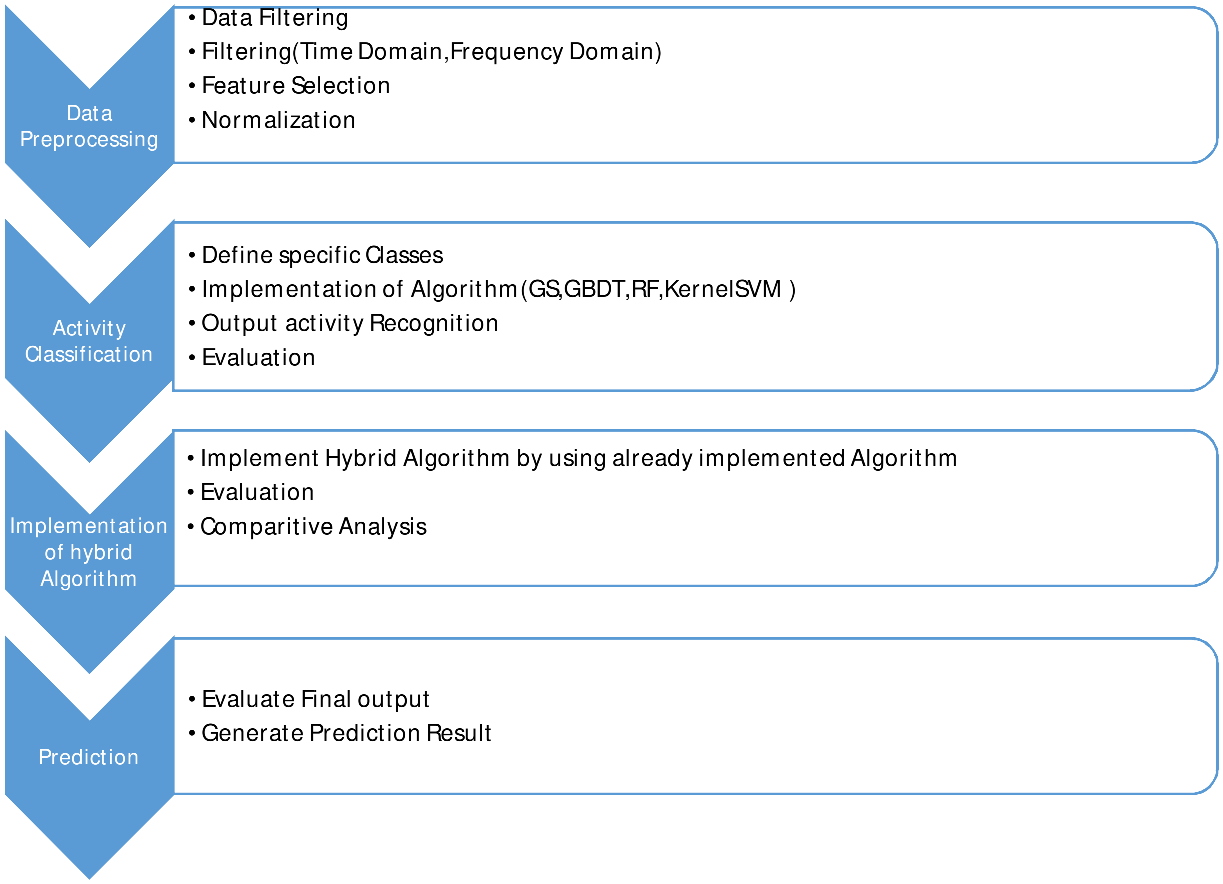
IV. ACTIVITY RECOGNITION METHODOLOGY

Various steps included in activity recognition



V. CONCLUSION AND FUTURE PERSPECTIVE

HAR remains one of the most challenging domains for th researcher owing to the complexity involved in the recognition of activities and the number of inhabitants present. Initial research on HAR has been considered a conventional pattern recognition problem. Traditional classification techniques SVM and Hidden Markov models have been extensively used in activity recognition systems. The traditional methods (shallow learning) are heavily dependent on human knowledge of the domain and also require feature engineering from the data, which is heuristic driven and. which involves a sequence of several micro activities using shallow learning However, deep learning methods learn the features directly from the data hierarchically which eliminated the problem of hand-crafted feature approximations. In addition, deep learning such as Convolutional Neural Networks has been successful in learning complex activities due to its properties of local dependencies and scale-invariance from one domain to another. In effect, extracting interesting's from one model to another allows the new model should be trained with reduced training samples, and hence the computational cost is reduced tremendously.

REFERENCES

[1] Mai, D.; Hoang, K. Motorbike theft detection based on object detection and human activity recognition. In Proceedings of the 2013 International Conference on Control, Automation and Information Sciences (ICCAIS), Nha Trang, Vietnam, 25–28 November 2013. [CrossRef]

[2] Ka ́ntoch, E. Human activity recognition for physical rehabilitation using wearable sensors fusion and artificial neural networks. In Proceedings of the 2017 Computing in Cardiology (CinC), Rennes, France, 24–27 September 2018. [CrossRef]

[3] Nursultan, N.R.; Selamaj, G. Random Forest for Human Daily Activity Recognition. J. Phys. Conf. Ser. 2020, 1655, 012087. [CrossRef]

[4] Mehmood, R.; See, S.; Katib, I.; Chlamtac, I. (Eds.) Smart Infrastructure and Applications: Foundations for Smarter Cities and Societies; Springer International Publishing: Berlin/Heidelberg, Germany, 2020; p. 692.

[5] Supriyatna, T.B.; Nasution, S.M.; Nugraheni, R.A. Human activity recognition using support vector machine for automatic security system. J. Phys. Conf. Ser. 2019, 1192, 012017. [CrossRef]

[6] Gao, Z.; Liu, D.; Huang, K.; Huang, Y. Context-aware human activity and smartphone position-mining with motion sensors. Remote Sens. 2019, 11, 2531. [CrossRef]

[7] Bragança, H.; Colonna, J.G.; Lima, W.S.; Souto, E. A smartphone lightweight method for human activity recognition based on information theory. Sensors 2020, 20, 1856. [CrossRef] [PubMed]

[8] Uddin, M.T.; Uddiny, M.A. A guided random forest based feature selection approach for activity recognition. In Proceedings of the 2015 International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Savar, Bangladesh, 21–23 May 2015. [CrossRef]

[9] Alawneh, L.; Alsarhan, T.; Al-Zinati, M.; Al-Ayyoub, M.; Jararweh, Y.; Lu, H. Enhancing Human Activity Recognition Using Deep Learning and Time Series Augmented Data. Available online: https://link.springer.com/article/10.1007/s12652-020-02865 -4#citeas (accessed on 8 July 2021).

[10] Kerboua, A.; Batouche, M.; Debbah, A. RGB-D & SVM action recognition for security improvement. In Proceedings of the Mediterranean Conference on Pattern Recognition and Artificial Intelligence, Tebessa, Algeria, 23–14 November 2016; pp. 137–143. [CrossRef]

[11] Bustoni, I.A.; Hidayatulloh, I.; Ningtyas, A.M.; Purwaningsih, A.; Azhari, S.N. Classification methods performance on human activity recognition. J. Phys. Conf. Ser. 2020, 1456, 12027. [CrossRef]

[12] Alam, F.; Almaghthawi, A.; Katib, I.; Albeshri, A.; Mehmood, R. iResponse: An AI and IoT-Enabled Framework for Autonomous COVID-19 Pandemic Management. Sustainability 2021, 13, 3797. [CrossRef]

[13] Balli, S.; Sa ˘gba¸s, E.A.; Peker, M. Human activity recognition from smart watch sensor data using a hybrid of principal component analysis and random forest algorithm. Meas. Control 2019, 52, 37–45. [CrossRef]

[14] D'Angelo, G.; Palmieri, F. Enhancing COVID-19 Tracking Apps with Human Activity Recognition Using a Deep Convolutional Neural Network and HAR-Images. Available online: https://link.springer.com/article/10.1007/s00521-021-05913-y (accessed on 8 July 2021).

[15] Yigitcanlar, T.; Butler, L.; Windle, E.; Desouza, K.C.; Mehmood, R.; Corchado, J.M. Can Building 'Artificially Intelligent Cities' Safeguard Humanity from Natural Disasters, Pandemics, and Other Catastrophes? An Urban Scholar's Perspective. Sensors 2020, 20, 2988. [CrossRef]

[16] Palaniappan, A.; Bhargavi, R.; Vaidehi, V. Abnormal human activity recognition using SVM based approach. In Proceedings of the International Conference on Recent Trends in Information Technology, ICRTIT 2012, Chennai, India, 19–21 April 2012; pp. 97–102. [CrossRef]

[17] Alomari, E.; Katib, I.; Mehmood, R. Iktishaf: A Big Data Road-Traffic Event Detection Tool Using Twitter and Spark Machine Learning. Available online: https://link.springer.com/article/10.1007%2Fs11036-020-01635-y (accessed on 8 July 2021).

[18] Batty, M. Artificial intelligence and smart cities. Environ. Plan. B Urban Anal. City Sci. 2018, 45, 3–6. [CrossRef]

[19] Yigitcanlar, T.; Kankanamge, N.; Regona, M.; Ruiz Maldonado, A.; Rowan, B.; Ryu, A.; Desouza, K.C.; Corchado, J.M.; Mehmood, R.; Li, R.Y.M. Artificial intelligence technologies and related urban planning and development concepts: How are they perceived and utilized in Australia? J. Open Innov. Technol. Mark. Complex. 2020, 6, 187. [CrossRef]

[20] Jobanputra, C.; Bavishi, J.; Doshi, N. Human Activity Recognition: A Survey. Procedia Comput. Sci. 2019, 155, 698–703. [CrossRef]

[21] Ogbuabor, G.; La, R. Human Activity Recognition for Healthcare using Smartphones. In Proceedings of the 2018 10th International Conference on Machine Learning and Computing, Macau, China, 26–28 February 2018. [CrossRef]

[22] Wang, H.; Zhao, J.; Li, J.; Tian, L.; Tu, P.; Cao, T.; An, Y.; Wang, K.; Li, S. Wearable Sensor-Based Human Activity Recognition Using Hybrid Deep Learning Techniques. Secur. Commun. Netw. 2020, 2020, 2132138. [CrossRef]

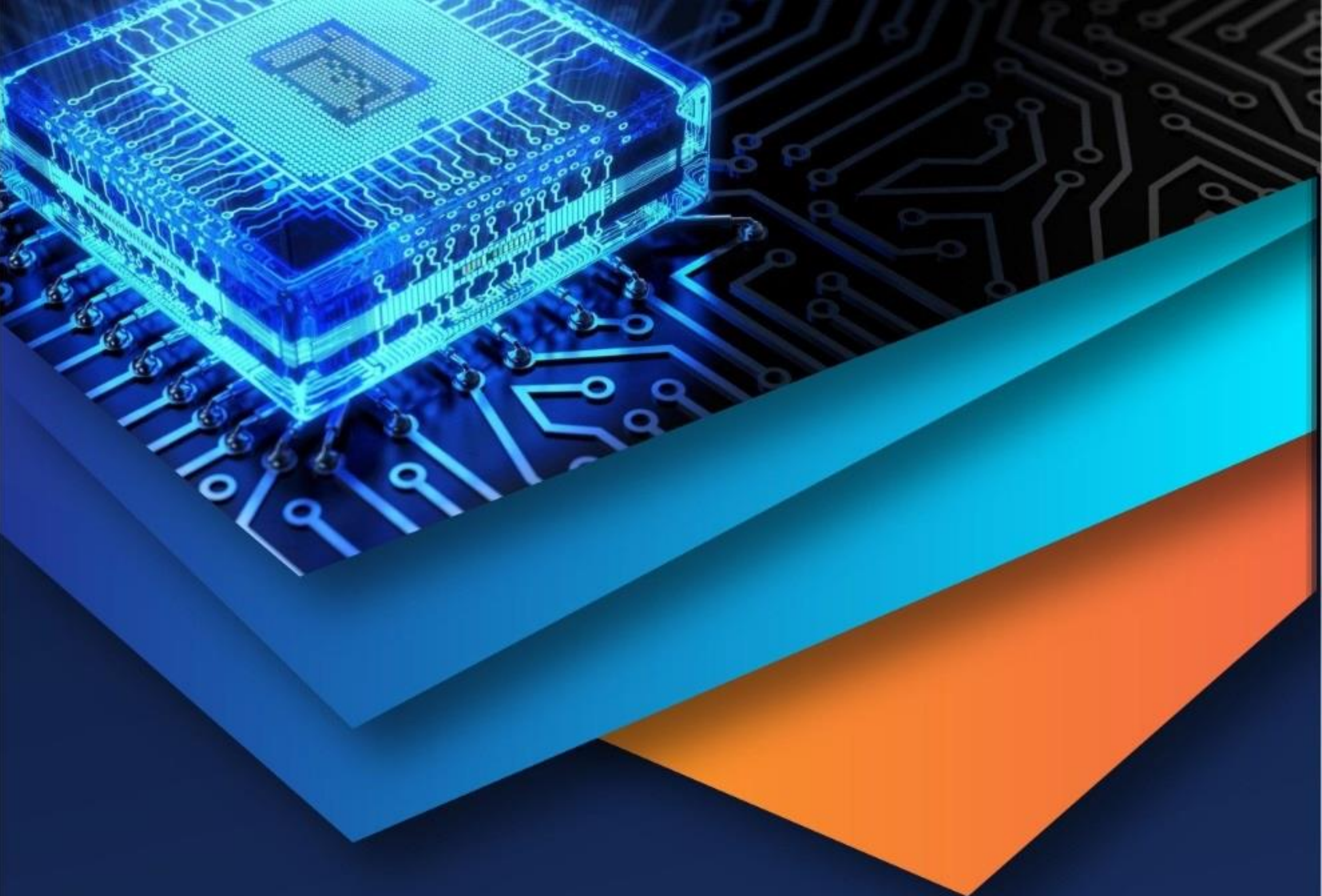
[23] Mehmood, R.; Alam, F.; Albogami, N.N.; Katib, I.; Albeshri, A.; Altowaijri, S.M. UTiLearn: A personalised ubiquitous teaching and learning system for smart societies. IEEE Access 2017, 5, 2615–2635. [CrossRef]

[24] Htike, K.K.; Khalifa, O.O.; Ramli, H.A.M.; Abushariah, M.A.M. Human activity recognition for video surveillance using sequences of postures. In Proceedings of the The Third International Conference on e-Technologies and Networks for Development (ICeND2014), Beirut, Lebanon, 29 April–1 May 2014. [CrossRef]

[25] Beddiar, D.R.; Nini, B.; Sabokrou, M.; Hadid, A. Vision-based human activity recognition: A survey. Multimed. Tools Appl. 2020, 79, 30509–30555. [CrossRef]

[26] Arfat, Y.; Usman, S.; Mehmood, R.; Katib, I. Big data for smart infrastructure design: Opportunities and challenges. In Smart Infrastructure and Applications Foundations for Smarter Cities and Societies; Springer: Cham, Switzerland, 2020; pp. 491–518. Algorithms 2021, 14, 245 16 of 17

[27] Anguita, D.; Ghio, A.; Oneto, L.; Parra, X.; Reyes-Ortiz, J.L. A Public Domain Dataset for Human Activity Recognition Using Smartphones. In Proceedings of the 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Bruges, Belgium, 24–26 April 2013; pp. 24–26.



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