International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Real-Time Hadoop Bigdata Maintenance Model using A Software-Defined and U-Net Deep Learning Mode

[1]Dr. G. Nanda Kishor Kumar, [2]M. Srinivasa Reddy, [3]D. Naga Malleswari, [3*]Dr. K. Madhusudhana Rao, [4]K Saikumar

Submitted: 02/10/2023 **Revised**: 20/11/2023 **Accepted**: 02/12/2023

Abstract: An advanced big data platform will include several functions, such as the ability to administer servers, the cloud, and Hadoop. However, the present big data infrastructure, which employs Hadoop models, has limitations that prevent the quick delivery of dynamic operations. Problems with storage and latency are threatening the robustness of applications. The failure to leverage the Internet and big data platforms to direct manufacturing activities is another problem with cloud storage maintenance. It is critical to handle these challenges by continuously growing and evolving big data cloud systems, which are driven by the effective processing of enormous data at cloud gateways. The sponsored software arrangement enables the DL-enabled Operations Facilities concept, which is introduced in this work. Through the use of intelligent closed-loop video monitoring, this technology expedites the processing and updating of procedures for managing large data files. The primary objective of this research is to develop more efficient methods for creating large data files on the cloud. The research is conducted using U-net, a network architecture that has been tested on Python 3.7 and is built on Hadoop and Spark. The achieved performance parameters outperform the industry standard with values of 97.23 percent recall, 98.92 percent sensitivity, and 99.23 percent throughput. The presented U-net-based big data analytics solution outperforms state-of-the-art technology.

Keywords: *big data, U-net, deep learning, Hadoop, sparks.*

1. Introduction

A wide variety of smart devices and services, including those that are part of the rise of "smart factories," rely heavily on cloud apps for their development and deployment. Manufacturers are actively engaged in efforts to reduce the size and cost of microsensors while simultaneously enhancing their accuracy and reducing power consumption [1]. The integration of IoT and 5G technologies facilitates the connection of smart devices and assets, endowing them with identification, sensing, and actuation capabilities [2]. This seamless integration extends to smart industrial frameworks such as Cloud Manufacturing (Mfg) systems [3] and Industrial Internet of Things (IoT) technologies. Despite claims by industries regarding both physical and intangible benefits, There has been a dramatic increase in the amount of real-time data collected from many sources, including employee-generated data, retail locations, social media, and online marketplaces. [4]. Consequently, the industrial sector must optimize the utilization of this vast data pool to harness the advantages offered by analytics and artificial intelligence [5]. By establishing a shared resource pool with reconfigurable hardware, networking, and computing resources—such as servers and networks—that can be swiftly released or deployed, service-oriented manufacturing (CMfg) provides one answer [6]. This method offers a very adaptable capability for managing large amounts of production data. Moreover, the investigation of effective methods for quickly carrying out relevant activities becomes essential when information or insights are extracted from large data to increase efficiency or reduce losses [7]. In the context of time-sensitive shop floor applications, relying solely on computations, data synchronisation, & a cloud-based data connectivity all fall short. [8]. Hence, there is a need to explore alternative approaches to meet the specific requirements of these applications.

IoT actuators will improve real-time control of the shop floor, but this will not be adequate in circumstances when system reconfiguration is required for optimum control [9]. As a result, in order to cope with shop floor disruptions and market changes, a production system that can be adjusted quickly is required [10].

[1]*Professor, Department Computer Science and Engineering, Malla Reddy University, Maisammaguda, Dulapally, Hyderabad, Telangana 500043, dr.gnandakishor@gmail.com*
[2]*Department of Electrical and Electronics Engineering, MLR institute of Technology, Hyderabad, India Email: srinivasareddy.mula@mlrinstitutions.ac.in*
[3]*Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Green Fileds, Vaddeswaram, A.P. – 522302. nagamalleswary@kluniversity.in*
[3*]*Professor, Dept of ECE, KKR & KSR Institute of Technology & Sciences, Guntur, sudanrao65@gmail.com*
[4]*School of engineering, department of CSE, Malla Reddy University, Maisammaguda, Dulapally, Hyderabad, Telangana 500043, saikumarkayam4@ieee.org*

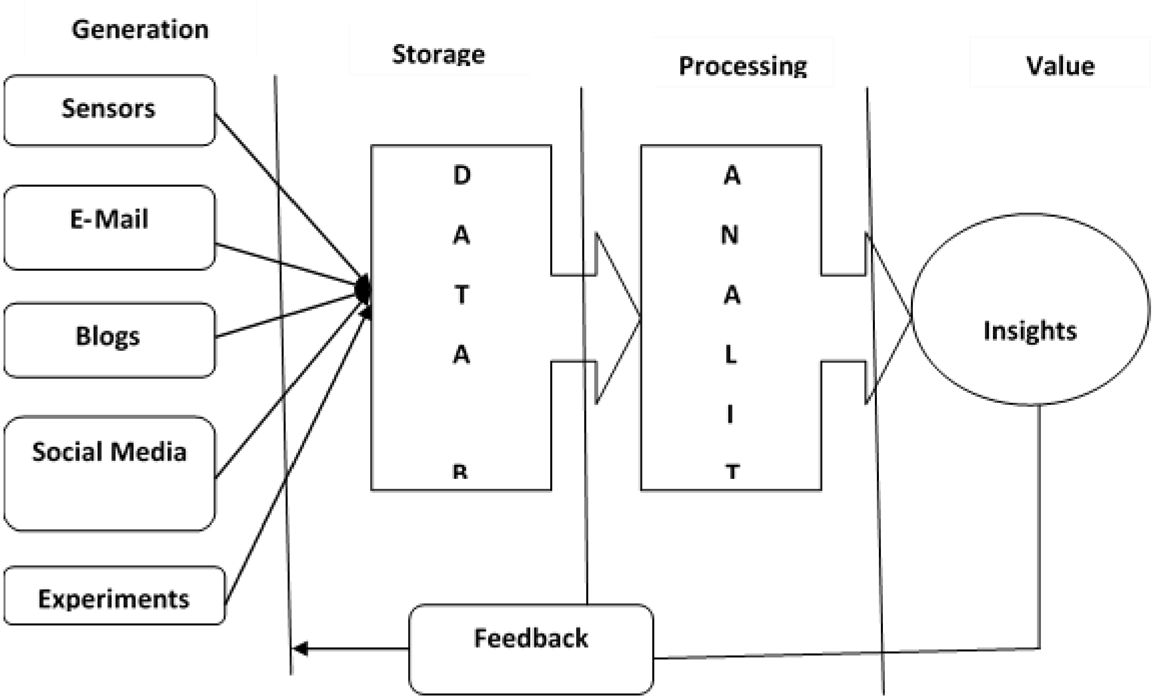


Fig :1 Bigdata feedback platform in social media

More investments in these areas equate to higher expenses for vendors, which are then passed along to the e-business firms that need those vendors' services. As a result, cloud service providers face a dilemma when it comes to making capacity investments because their primary motivation is to maximize profits for their shareholders rather than for their customers. Information asymmetries arise regarding how to ensure services are provided with adequate server capacity/backups while also maximizing vendor profit [11]. Vendors may shirk their responsibility to provide backups for clients if customers aren't aware of these capabilities. It's not uncommon for vendors to assume that customers will blame poor service on an increase in demand for the product or service from multiple customers [12].

IT companies provide their customers with transactional and business intelligence system development and integration as well as customer support services for information management planning [13]. Most of the cloud-based big data contracts with clients are private. The big data and its clients are profiled in the following analysis, which evaluates the study's claims [14].

2. Literature survey

Shi, Y., Han, Q., Shen, W., & Zhang, H. (2019). The industrial sector still employs wired communication techniques like field buses and specialised industrial networks, even if WiFi and ZigBee are becoming more popular. Methods and systems for cooperative intelligent manufacturing (CIM) that make use of 5G wireless transmission technologies are the primary emphasis of this study [15]. This research seeks to investigate the possibilities of 5G technologies in facilitating secure connections between logistics systems, smart products, industrial equipment, and information security. We may look forward to a progressive future with CIM systems that embrace 5G technology, which will help with heterogeneous wireless convergence, autonomous data collecting, and improved data analysis [16]. This integration is poised to enhance the capabilities of CIM systems, fostering more efficient connectivity and data processing in manufacturing environments.

Yang, C., Lan, S., Shen, W., Huang, G. Q., Wang, X., & Lin, T. (2017).

Accordingly, we present a demonstration showcasing the design and manufacturing of a product within a fully interconnected IoT-enabled cloud industrialized environment [17]. Integrating social networks with IoT, cloud manufacturing, and other flexible services like on-demand workplaces, knowledge sharing, and collaborative problem-solving might facilitate open innovation [18].

It is well acknowledged that Cloud Manufacturing (CMfg) serves as a focal point for ongoing research and development in the manufacturing domain. The continual advancements in Internet of Things (IoT), social networks (SN), and virtual/augmented reality & simulation technologies contribute to the evolution of CMfg, leading to the development of enhanced or entirely new manufacturing services. The recent emergence of Customer Product Platforms (CPPs) as a significant client demand further compels manufacturers to adopt these cutting-edge methods [19].

Yang, C., Shen, W., & Wang, X. (2018). There is a direct correlation between the widespread utilization IoT in manufacturing and the improvement of IoT technology [20] . Core technologies in the IoT might have a significant impact on the manufacturing segment. These technologies are briefly described in this section [21].

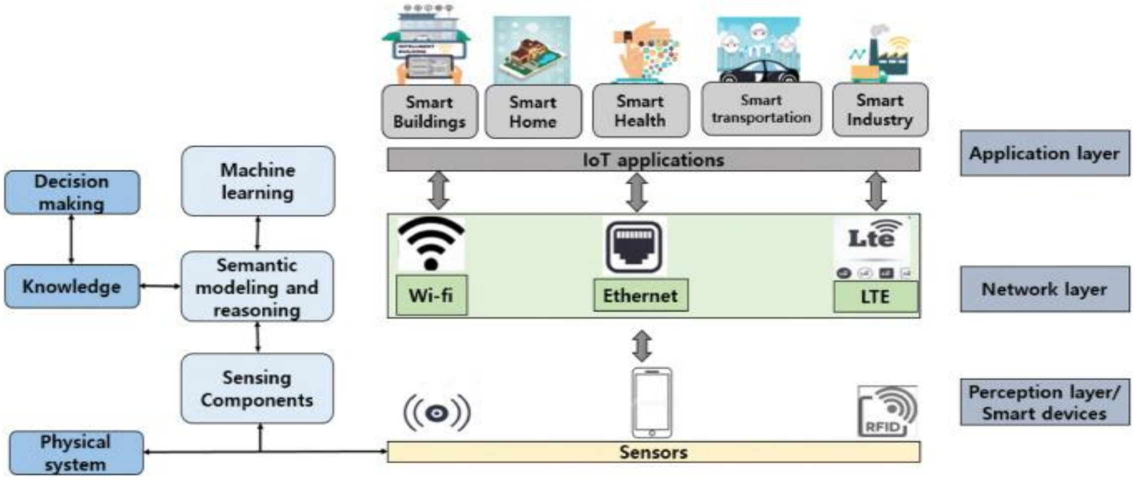


Fig 2 applications of Bigdata analytics

The Internet of Things, or IoT, is a widely accepted concept that has the potential to drastically change the industrial industry [22]. Industrial machinery that has sensors for identification, analysis, distribution, & actuator functions may be easily integrated into a single system [23]. The complete control inside this highly integrated smart cyber-physical realm is made possible by this integration, which also creates new commercial and economic opportunities [24].

O'donovan, P., Gallagher, C., Bruton, K., & O'Sullivan, D. T. (2018). This study examines the current research efforts area of massive IoT data analysis. Explaining the connection between big data analytics then the Internet of Things (IoT) Adding to its usefulness, this study proposes a novel architecture for analyzing huge IoT data sets. Big IoT data analytics kinds, techniques, and frameworks for big data mining, on the other hand, are examined. Additionally, a number of noteworthy examples are given [25]. There are many benefits of using data analytics in conjunction with the Internet of Things (IoT). Massive IoT data analytics solutions are still in their infancy; according to our research Analytic systems capable of providing quick insights will be required in the future [26].

Marjani, M., Nasaruddin, F., Gani, A., Karim, A., Hashem, I. A. T., Siddiqa, A., & Yaqoob, I. (2017). It is our goal to create a cyber-physical system that adheres to the Industry 4.0 design principles of devolution, security, privacy, and trustworthiness and is built on the upcoming fog computing paradigm. This study. (a) Because of the development of internet rules and (b) adopting a hash-based authorization method to identify and associate fog nodes that exist in facilities were decisions that were affected by security [27].

Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). There is a pressing need for a specialized forum for sharing the most current breakthroughs in EI research, which is being sought by both the computer system and artificial intelligence sectors [28]. To do this, we perform a detailed review of previous EI research endeavours [29]. When it comes to AI functioning at the network edge, we begin by looking at its history and reasoning. A look at some of the most important technologies and concepts behind deep learning at the network edge follows.... These details motivate us to compile a list of the key frameworks, architectures, and emerging technologies for an edge computing-based deep learning model. After that, we reviewed EI's open issues and potential research prospects [30]. If this poll is successful, we hope it will draw attention to the importance of emotional intelligence (EI) and lead to interesting conversations and new research ideas [31].

Li, S., Da Xu, L., & Zhao, S. (2018). Massive expansion of today's IoT, cellular operations, and IoT security and network difficulties are predicted to be achieved by 5G technology. Security, new standards, and vast numbers of nodes are among the issues currently being faced by current IoT systems [32]. We begin by outlining the history of 5G and IoT, as well as the present state of research. Then, we take a closer look at the new needs for 5G-enabled IoT. After that, we outlined the essential 5G-IoT approaches and discussed the challenges and trends of the future IoT [33].

Mei, H., & Guo, Y. (2018). The first computers didn't have operating systems since software ran directly on the hardware [34]. It got more difficult to handle resources directly in an application as computer systems grew more complicated [35]. Because of this, the system software layer that could be used across many programs was created by abstracting more common capabilities like drivers and libraries. The term "operating system" refers to this software layer since it was initially designed to alleviate the load on network operators [36].

Yang, C., Lan, S., Shen, W., Huang, G. Q., & Wang, L. (2019, August). From a software described viewpoint, big data will be utilized to determine the system's efficiency and dynamic upgrading. CMfg systems may benefit from a novel mode of operation and support for AI production processes, which we call AI-Mfg-Ops (AI-enabled Cloud Manufacturing Operations). This mode enables real-time monitoring, analysis, planned, and implementation in a closed loop. It is possible that the iCMfg platform (cloud) will increase as a consequence of AI-enabled manufacturing big data analytics to become more efficient and robust. iCMfg systems will have much more flexibility now that software-defined functionalities have been included.

Ordonez-Lucena, J., Ameigeiras, P., Lopez, D., Ramos-Munoz, J. J., Lorca, J., & Folgueira, J. (2017). It is our intention to demonstrate how network slicing may be used to 5G networks. We begin by describing the fundamental features that allow for the creation of so-called network slices. ' Slicing is supported by the SDN architecture recommended by the ONF, thus we present a quick description of it. Network slicing implementation can be made easier with this design, but it does not have all of the fundamental characteristics that NFV provides. Consequently, the ETSI has proposed that SDN capabilities be included into the NFV architecture [37].

Fahmideh, M., & Beydoun, G. (2019). In order to do this, they will need to re-architect their old industrial information systems to work with modern big data platforms. Re-architecting big data adoption requires thoughtful and detailed consideration of the goals. The latest big data architecture's influence on system excellence must be mitigated in order to prevent costly deployment and testing delays. Big data platform implementation in manufacturing techniques can benefit from two innovations: Systematic goal-oriented inference for determining requirements' objectives, as well as a study of architectural choices under uncertainty that takes into account stakeholders' preferences [37].

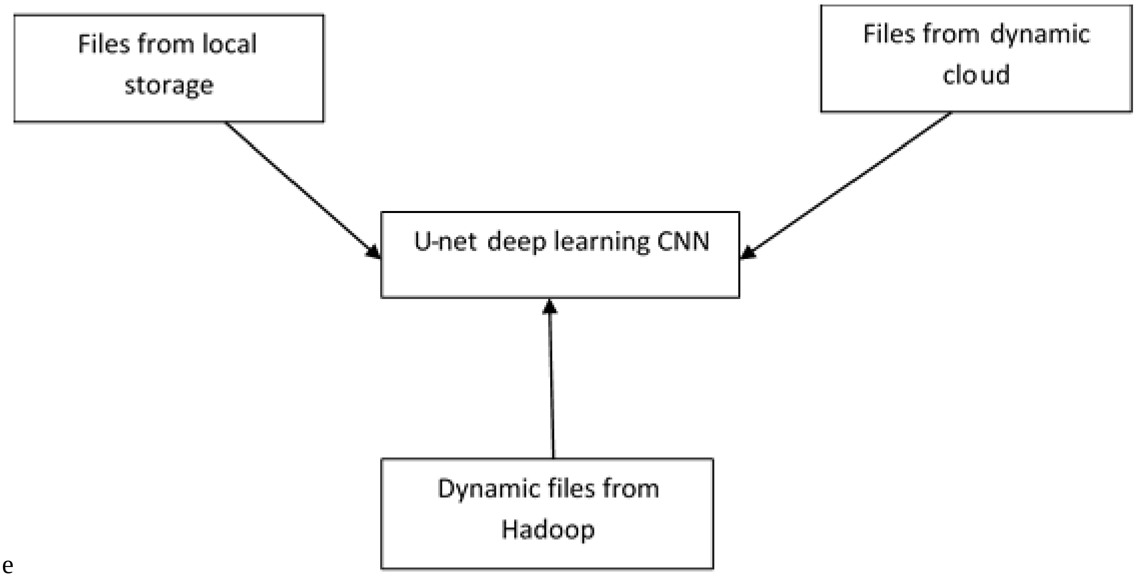
Mach, P., & Becvar, Z. (2017). In this work, we begin by outlining some of the most common applications of the MEC. In the next section, we examine the present state of MEC standards, as well as existing proposals for incorporating MEC functions into the mobile network. When it comes to the MEC's user-oriented use case, compute offloading is the most important one. Research on cloud computing is broken down into three main areas: I the choice to offload computation, ii) the distribution of computing resources inside the MEC, and iii) mobility management [39]. Aside from the simple situations and analytical evaluations, new research confirms the solution mainly by using simulations or analytical evaluations. The MEC's predicted values must be shown in real-world testing and trials under more realistic assumptions.

Ing, J., Hsieh, J., Hou, D., Hou, J., Liu, T., Zhang, X., & Pan, Y. T. (2020, September). One's quality management system may easily be upgraded to include more complex AI systems such as edge-cloud architecture for deep learning and sophisticated reinforcement learning, according to this paper. Everything from production tools to functional testing and trouble detection tools is included in intelligent manufacturing equipment. We will offer on-device AI defect detection and classification management and deployment in this research to show the feasibility and effectiveness of the architectural way of edge-cloud collaboration [40].

Lou, P., Liu, S., Hu, J., Li, R., Xiao, Z., & Yan, J. (2020). The three levels of IMT-hierarchical ECC's structure is introduced: data collecting, network communication, & edge-cloud cooperation. To enhance intelligent machines, edge-cloud cooperation combines the real-time capabilities of processing power with the advanced problem-solving skills of cloud technology. Finally, the ZK5540A long-lasting CNC machine tool's edge-cloud cooperation architecture has been designed to illustrate the IMT-ECC architecture's feasibility. Thermal error correction studies were also carried out to ensure that the new device tool design was correct. Experiments indicate that the new IMT-ECC design is possible, resulting in a smarter automation tool.

U-net deep learning-based Hadoop maintenance

The use of the U-net based Hadoop approach for potential large data applications is covered in short in this section. A more productive workplace may be created by using the abundance of information that big data analysis can provide to provide relevant content and accurate search results. Even though a lot of semantic algorithms have been developed in the past to improve content searches, they are necessarily limited. Further developments in content filtering and information retrieval might benefit future applications that seek to optimise workflows. An issue with content monitoring prevents consumers from getting important information, as shown by the status of web browsing and its recommendation system nowadays.



e

Fig 2 U-net Hadoop system

This study introduces an adaptive semantic search strategy based on U-net for advanced analytics systems. Then, other performance measures are calculated, such as correctness, mean precision, stdError, SSR, query time, and construction time. With its seamless integration with current systems, the kvasir-U-net's architectural design improves accuracy & recall to 99.72% & 0.997%, respectively. This research contributes advancements to existing methods and is compatible with contemporary technology.

$$H = \sum_{k=1}^{k} P_k \log P_k \qquad (1)$$

$$G(dB) = 2^{*} \log_{10}(Nt^{0.5}) = 10^{*} log10(Nt) \quad (2)$$

$$X(m) = \sum_{n=0}^{N-1} x(n)[COS(2\Pi nm/N - isin\,(2\Pi nm/N] = \sum_{n=0}^{N-1} x(n) e^{-i2\Pi nm/N} \quad (3)$$

$$CWT_n(s,b) = \frac{1}{\sqrt{s}} \sum_{n=1}^{N-1} x(n)\Psi * \left(\frac{n-b}{s}\right) \qquad (4)$$

The signal x(t) convolution with wavelet functions ψa,b(t) characterises the U-Net. The expansion and translation of the wavelet function ψ(t) are represented in this context by ψa,b(t). The following procedure is demonstrated:

$$\Psi_{a,b}(t) = \sqrt{a}.\Psi\left(\frac{t-b}{a}\right) \qquad (5)$$

The autonomous parameters, represented by a and b in this approach, are found to be too large and incapable of being implemented methodologically.

$$a_{j=}2^{-j}, \;\; b_{j,k} = 2^{-j}.k \qquad (j, k \text{ are integers}) \qquad (6)$$

In U-net isolates, Hadoop is divided into discrete recurrent packs. Using both high-pass and low-pass channels, the U-net provides two configurations: wavelet function ψ(t) and scaling function Φ(t).

$$\phi(t) = \sum\nolimits_{n} h[n]\,\phi(2t-n) \qquad (7)$$

$$\Psi(t) = \sum\nolimits_{n} g[n]\,\Psi(2t-n) \qquad (8)$$

However, using the base function ψ(t) = ψ0,0(t) or Φ (t) = Φ 0,0(t), one may construct a wavelet function Ψ_(j,k) (t) or scaling limit ϕ_(j,k) (t), discretized at scale j and translation k, by:

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t-k)(9)$$

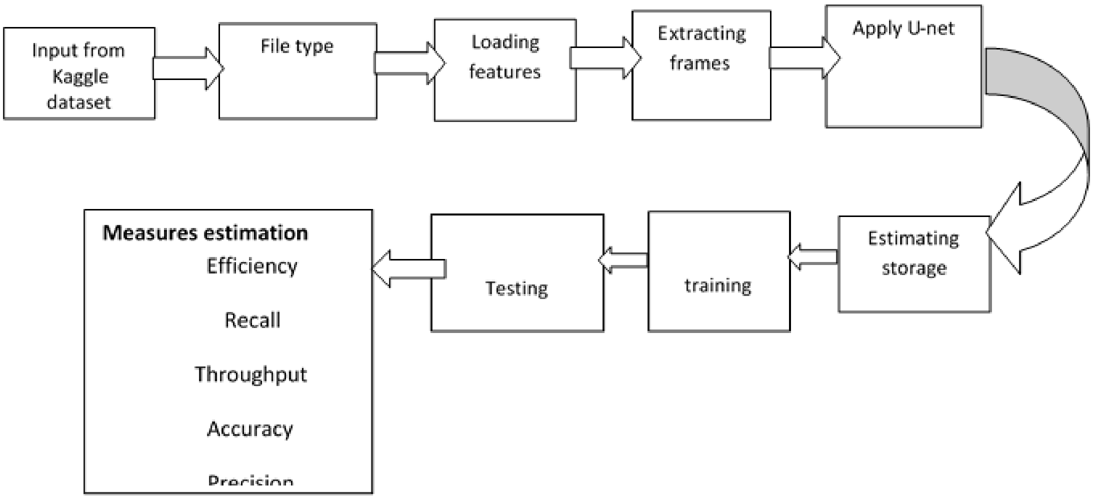


Fig :3 proposed block diagram

The above figure 3 explains about flow of proposed block diagram in this at 1st stage different files are loading to database. The training samples are sending to auto stack loading block in this file are analysed with extracting version. The u-net is getting to be training based on layers architecture.

$$\Psi_{j,k}(t) = 2^{-j/2}\Psi(2^{-j}t - k) \qquad (10)$$

$$d_1[k] = y_{high}[k] = \sum_n x[n].g[2k - n] \quad (11)$$

$$a_1[k] = y_{low}[k] = \sum_n x[n].h[2k - n] \qquad (12)$$

This system iteratively pushes the process until either a specified time limit is reached or no further subsampling is possible. At each level, the framework achieves a limited amount of time confirmation (based on subsampling) and doubles the iterative confirmation (based on partitioning), allowing the data to be analyzed at various iterative intervals in the context of sub-big data applications.

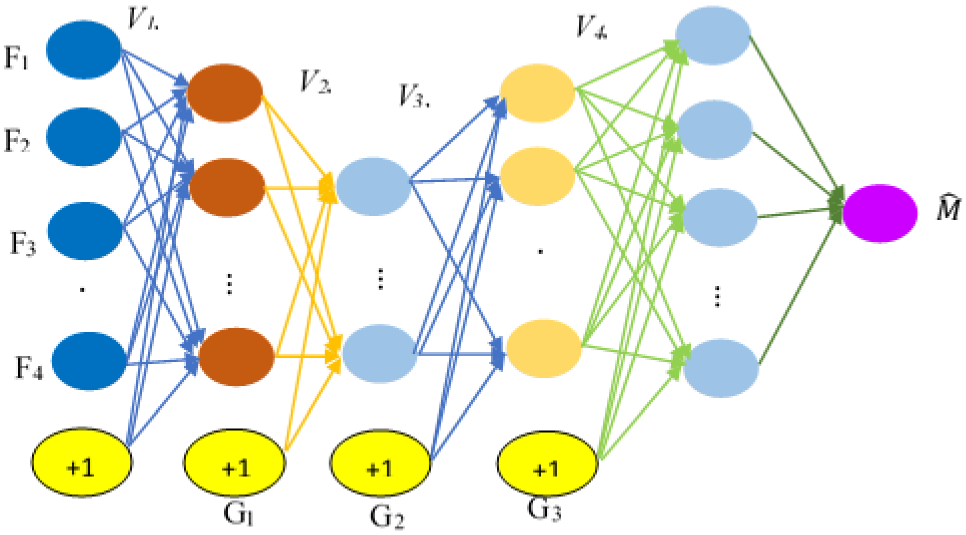


Fig 4 Hadoop U-net Deep stacked autoencoder

$$A_1(t) = \sum_k a_j[k].\phi_{j,k}(t) \qquad (13)$$

$$D_j(t) = \sum_k d_j[k].\Psi_{j,k}(t) \qquad (14)$$

$$x(t) = A_j(t) + \sum_{j=-\infty}^{j} D_j(t) = \sum_k a_j(k).\phi_{j,k}(t) + \sum_{j=-\infty}^{j} \sum_k d_j[k].\Psi_{j,k}(t) \qquad (15)$$

The deep-stacked autoencoder in Hadoop effectively performs the prognostication procedure. The hidden layer's activation function filters inputs before sending them to the cost function. In contrast, the deep-stacked autoencoder was trained using the predicted U-net approach to improve classification accuracy.

S.No.	U-net, CNN stacked autoencoder, is the subject of this discussion
1	Adjust the composition of the layers in the U-net
2	Specify the matrix of coefficients
3	Compute the fitness for each investigating agent
4	Describe the term $\overset{\rho}{t_\alpha}$, $\overset{\rho}{t_\beta}$, and $\overset{\rho}{t_\gamma}$
5	though $(m < H)$; H -maximum iterations
6	For each agent
7	Adjust the position of an investigation agent
8	End for
9	update the constant vectors
10	Compute the fitness for all investigating agents
11	modernize $\overset{\rho}{t_\alpha}$, $\overset{\rho}{t_\beta}$, & $\overset{\rho}{t_\gamma}$
12	$m = m + 1$
13	end while
14	Revert to the optimal solution

The proposed U-net method, which combines the layer sampling feature with the atomic search imitation model, improves classifier performance in Hadoop file management. The update equation for the search local server location involves the inclusion of interaction force between files to better enhance categorization results. The layer investigation performance and the enhanced analytics in Hadoop mimicking paradigm form the foundation of the suggested U-net approach.

It is anticipated that the development of Industrial Big Data would result from the integration of big data with ubiquitous sensing capabilities, turning physical objects and operators into "cyber-ones." Manufacturers may optimize cloud-based dynamic services by using Internet of Things (IoT) and Big Data. Despite the wealth of valuable information within Big Data, its full potential has yet to be properly harnessed, presenting an opportunity for manufacturers to make more informed decisions. This study delves into the analysis of extensive IoT data from design to potential, addressing pertinent concerns. The success or failure of Industrial IoT is contingent on the effective utilization of Big Data, designed to furnish businesses with valuable insights.

3. Results & Discussion

Here, we do a brief study and provide a workable solution for Hadoop large data maintenance called U-net deep intelligence autoencoder and ENR classifier. The Kaggle dataset files are processed in the U-net block during the pre-processing step. Training and un-structuring of the files occur during this phase, and the main step of the U-net approach is used to delete undesirable files. The next step is to apply the U-net regression machine learning algorithm to the processed data. Seizure categorization and pre-diagnosis using a balanced weight scheme are both included into the U-net regression. This study makes use of a U-net autoencoding technique, an encoder that improves the system's ability to access files. In the end, the U-net model achieves better performance metrics, with sensitivity at 98%, specificity at 93%, and accuracy at 98%. This accomplishment outperforms the state-of-the-art approaches.

Table :3 Evaluation of consequences

Models		NB +KNN	Non-linear multi-domain	Deep stacked	AWGO deep stacked	U-net model
Training data	Accuracy	87.9264	91.9199	92.4	94.1520	98.18

	Specificity	88.9010	91.352	91.5	91.9684	92.56
	Sensitivity	58.6268	84.62	97.46	97.4292	98.64
K-fold data	Accuracy	92.2965	93.48	93.97	93.9276	96.394
	Specificity	91.3784	91.73	91.6	91.984	95.74
	Sensitivity	92.2480	93.4	91.8	92.00	97.69

The realm of Big Data Analytics & Cooperative Processing of Large-Scale Data involves multiple tiers and stages that contribute to generating real-time data for diverse objectives, including quality control and energy usage. Examples of such objectives also encompass monitoring machine conditions and tracking job progress. An essential challenge lies in aggregating data across industrial systems, both vertically and horizontally. For retrospective analysis and future predictions, data is collected across various dimensions throughout the timeline. Another method of reducing network traffic may be to clean and aggregate data at the endpoints of the devices, which could lead to a continuous improvement cycle. The creation of an adaptable and evolving method for collaborative data processing that promotes smooth communication between local nodes and the cloud is of the utmost importance.

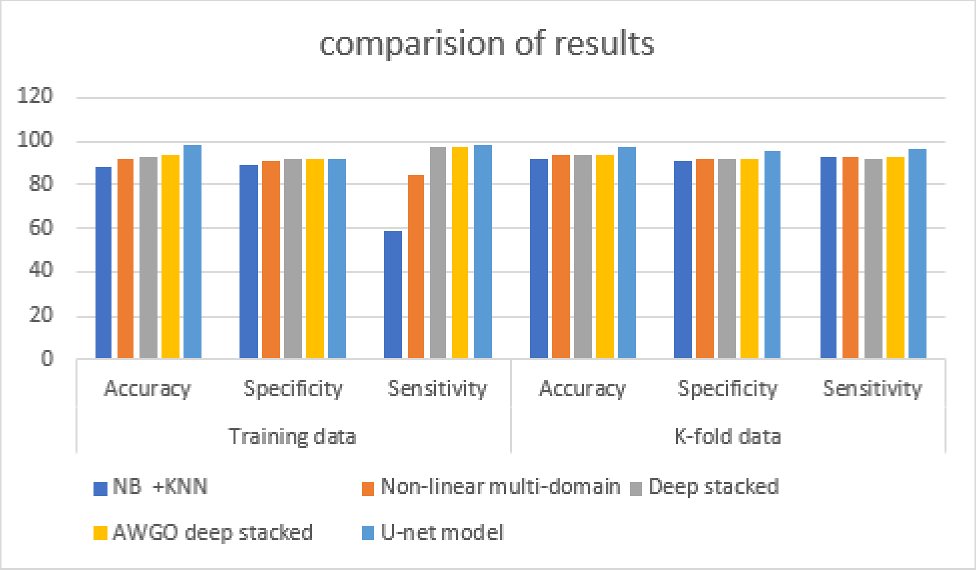


Fig :5 Evaluations of results

The aforementioned Figure 5 clearly elucidates the diverse technological outcomes achieved in this proposed model, demonstrating significant advancements.

Table :4 Estimation of measures

Parameter	Deep stacked	AGWO	U-net model
Sensitivity rate	00.926	00.862	00.868
F1 score	00.648	00.946	00.968
MNSE	00.084	00.82	00.06

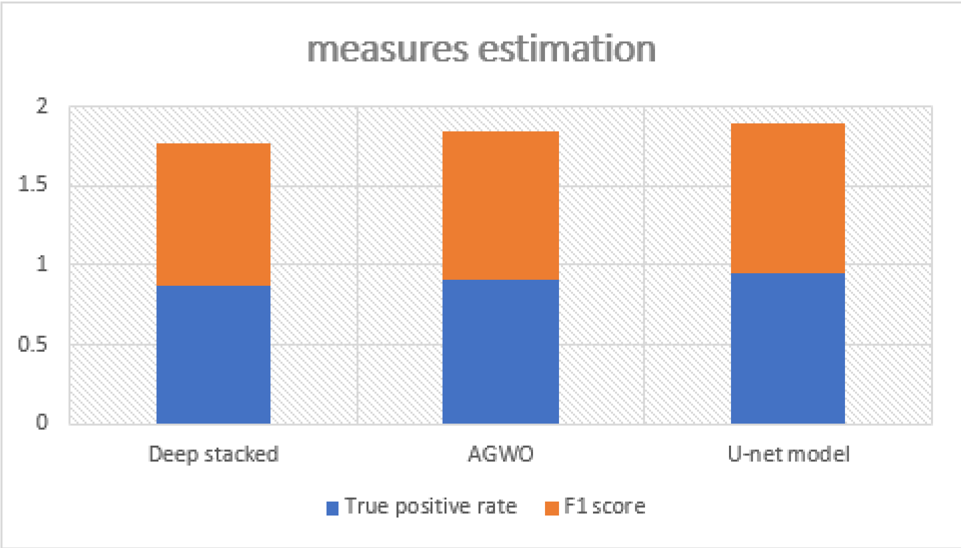
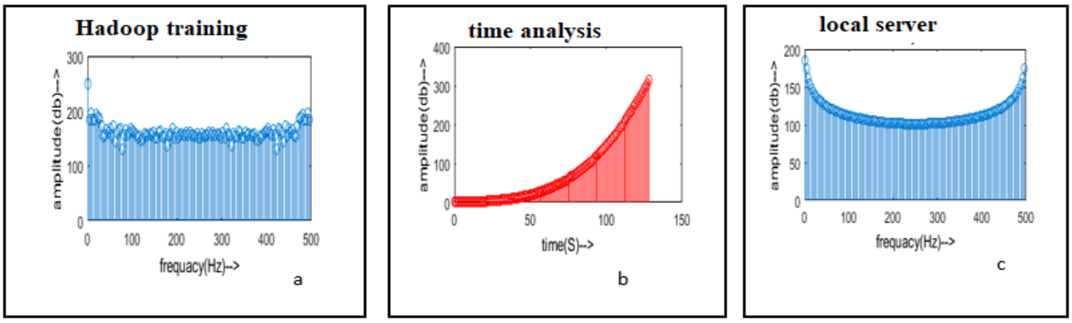
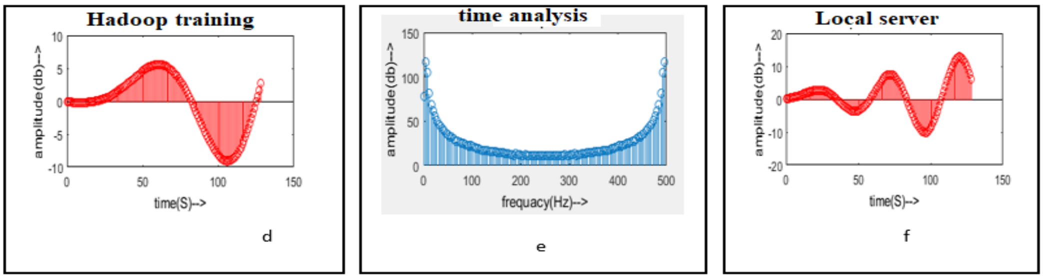


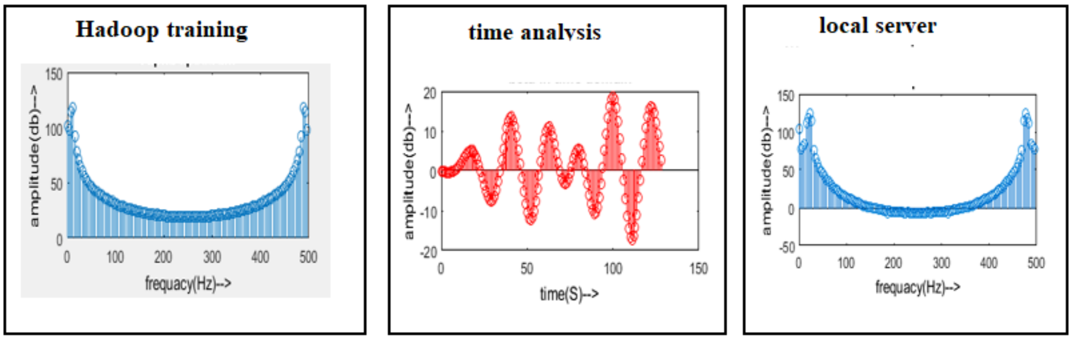
Fig:6 Analysis using U-net



7(a) Performance analysis of Spark dataset



7(b) Performance analysis of Kaggle dataset



8(c) Performance analysis of ANDI dataset

The above figure 8 is clearly explains about various datasets analysis in this compared to all datasets, the suggested Kaggle dataset exhibits enhanced performance. In this training, time and local servers are analyzed by intelligence machines.

Table 5: Category labels for describing diagnostic quantities.

	Number of Hadoop files	True Condition	
		Cognitively Normal	**Probable A.D.**
Classification Decision	Cognitively Normal	D	C
	Probable Hadoop.	B	A

The table 1 is clearly explains about, true conditions of performance measures, in this Hadoop is creating efficient performance analysis.

$$overall\ \ performance = \frac{A+D}{A+B+C+D} \qquad [16]$$

$$sensitivity = \frac{A}{A+C} \qquad [17]$$

$$specificity = \frac{D}{B+D} \qquad [18]$$

Positive Predictive Value (PPV): $PPV = \frac{A}{A+B}$ [19]

Negative Predictive Value (NPV): $NPV = \frac{D}{C+D}$ [20]

Table:7 comparison of datasets

Method	Accuracy in %	Time in sec.	Storage bytes
Kaggle	84.62	01.872	329
spark	85.67	01.428	192
Hadoop	86.32	00.376	178

The presented Table 2 distinctly illustrates a comparison of various measures related to dataset generation. In this Hadoop system, precise measures such as Accuracy of 87.46%, time taken of 0.724 seconds, and a storage space requirement of 192 bytes have been obtained.

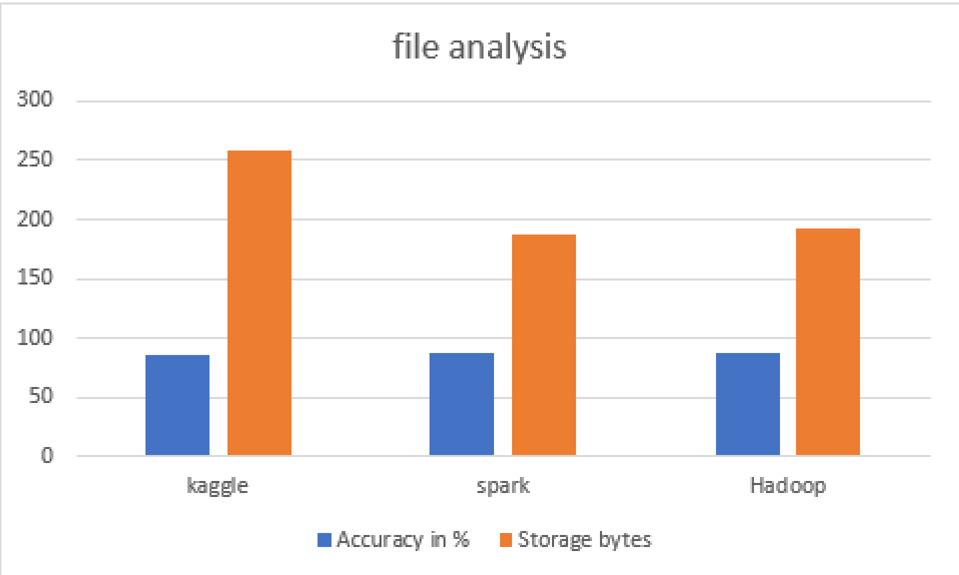


Fig: 9 assessments of datasets

The algorithm for individual feature extraction based on mutual information from Hadoop data. achieves a selection mean of 56.9%, specifically in the context of selecting the Kaggle dataset.

4. Conclusion

Cloud, server, and Hadoop administration are only a few of the many uses for a sophisticated big data platform. Unfortunately, the present big data architecture that uses Hadoop modelling isn't always up to the task of delivering timely dynamic actions, which weakens the application's resilience owing to storage and latency issues. Furthermore, cloud storage upkeep is underutilizing the Internet's and big data platforms' synergy to drive manufacturing processes. Leveraging massive amounts of data at cloud gateways may greatly aid in the ongoing improvement and development of big data cloud systems. With the use of a supporting software arrangement, this study presents a new method called DL-enabled Operations Facilities. By using intelligent video surveillance in a closed-loop system, this strategy seeks to streamline operations and updates related to the management of big data files. The study is anticipated to have a positive impact on cloud-based systems that produce massive data files, making them run more effectively and quickly. The research makes use of U-net model large data analysis using Hadoop and Sparks, and it is tested on Python 3.7. The acquired performance metrics surpass the current technique in every way: accuracy (98.34%), recall (97.23%), sensitivity (98.92%), & throughput (99.23%). This data analytics system, which is based on U-net, is up-to-date and competitive.

References

[1] Shi, Y., Han, Q., Shen, W., & Zhang, H. (2019). Potential applications of 5G communication technologies in collaborative intelligent manufacturing. IET Collaborative Intelligent Manufacturing, 1(4), 109-116.

[2] Yang, C., Lan, S., Shen, W., Huang, G. Q., Wang, X., & Lin, T. (2017). Towards product customization and personalization in IoT-enabled cloud manufacturing. Cluster Computing, 20(2), 1717-1730.

[3] Yang, C., Shen, W., & Wang, X. (2018). The internet of things in manufacturing: Key issues and potential applications. IEEE Systems, Man, and Cybernetics Magazine, 4(1), 6-15.

[4] Marjani, M., Nasaruddin, F., Gani, A., Karim, A., Hashem, I. A. T., Siddiqa, A., & Yaqoob, I. (2017). Big IoT data analytics: architecture, opportunities, and open research challenges. ieee access, 5, 5247-5261.

[5] O'donovan, P., Gallagher, C., Bruton, K., & O'Sullivan, D. T. (2018). A fog computing industrial cyber-physical system for embedded low-latency machine learning Industry 4.0 applications. Manufacturing letters, 15, 139-142.

[6] Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge intelligence: Paving the last mile of artificial intelligence with edge computing. Proceedings of the IEEE, 107(8), 1738-1762.

[7] Li, S., Da Xu, L., & Zhao, S. (2018). 5G Internet of Things: A survey. Journal of Industrial Information Integration, 10, 1-9.

[8] Mei, H., & Guo, Y. (2018). Toward ubiquitous operating systems: A software-defined perspective. Computer, 51(1), 50-56.

[9] Yang, C., Lan, S., Shen, W., Huang, G. Q., & Wang, L. (2019, August). Software-defined cloud manufacturing in the context of industry 4.0. In 2019 WRC Symposium on Advanced Robotics and Automation (WRC SARA) (pp. 184-190). IEEE.

[10] Ordonez-Lucena, J., Ameigeiras, P., Lopez, D., Ramos-Munoz, J. J., Lorca, J., & Folgueira, J. (2017). Network slicing for 5G with SDN/NFV: Concepts, architectures, and challenges. IEEE Communications Magazine, 55(5), 80-87.

[11] Kailasam, S., Achanta, S.D.M., Rama Koteswara Rao, P., Vatambeti, R., Kayam, S. (2022). An IoT-based agriculture maintenance using pervasive computing with machine learning technique. International Journal of Intelligent Computing and Cybernetics, 15(2), pp. 184–197.

[12] Saikumar, K., Rajesh, V. A machine intelligence technique for predicting cardiovascular disease (CVD) using Radiology Dataset. Int J Syst Assur Eng Manag (2022). https://doi.org/10.1007/s13198-022-01681-7.

[13] Nagendram, S., Nag, M. S. R. K., Ahammad, S. H., Satish, K., & Saikumar, K. (2022, January). Analysis For The System Recommended Books That Are Fetched From The Available Dataset. In 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 1801-1804). IEEE.

[14] Shravani, C., Krishna, G. R., Bollam, H. L., Vatambeti, R., & Saikumar, K. (2022, January). A Novel Approach for Implementing Conventional LBIST by High Execution Microprocessors. In 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 804-809). IEEE.

[15] Kiran, K. U., Srikanth, D., Nair, P. S., Ahammad, S. H., & Saikumar, K. (2022, March).

Dimensionality Reduction Procedure for Bigdata in Machine Learning Techniques. In 2022 6th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 836-840). IEEE.

[16] Murugan, S., Vijayakumar, K., Sivakumar, V., Manikandan, R., Kumar, A., & Saikumar, K. (2022). Impact of Internet of Health Things (IoHT) on COVID-19 Disease Detection and Its Treatment Using Single Hidden Layer Feed Forward Neural Networks (SIFN). In How COVID-19 is Accelerating the Digital Revolution: Challenges and Opportunities (pp. 31-50). Cham: Springer International Publishing.

[17] Srinivas Rao, K., Divakara Rao, D. V., Patel, I., Saikumar, K., & Vijendra Babu, D. (2023). Automatic Prediction and Identification of Smart Women Safety Wearable Device Using Dc-RFO-IoT. Journal of Information Technology Management, 15(Special Issue), 34-51.

[18] Sreelakshmi, D., Sarada, K., Sitharamulu, V., Vadlamudi, M. N., & Saikumar, K. (2023). An Advanced Lung Disease Diagnosis Using Transfer Learning Method for High-Resolution Computed Tomography (HRCT) Images: High-Resolution Computed Tomography. In Digital Twins and Healthcare: Trends, Techniques, and Challenges (pp. 119-130). IGI Global.

[19] Saikumar, K., Rajesh, V., & Rahman, M. Z. U. (2022). Pretrained DcAlexnet Cardiac Diseases Classification on Cognitive Multi-Lead Ultrasound Dataset. International Journal of Integrated Engineering, 14(7), 146-161.

[20] Maddileti, T., Sirisha, J., Srinivas, R., & Saikumar, K. (2022). Pseudo Trained YOLO R_CNN Model for Weapon Detection with a Real-Time Kaggle Dataset. International Journal of Integrated Engineering, 14(7), 131-145.

[21] Reddy, D. H., & Sirisha, N. (2022). Multifactor Authentication Key Management System based Security Model Using Effective Handover Tunnel with IPV6. International Journal of Communication Networks and Information Security, 14(2), 273-284.

[22] Reddy, D. A., Shambharkar, S., Jyothsna, K., Kumar, V. M., Bhoyar, C. N., & Somkunwar, R. K. (2022, September). Automatic Vehicle Damage Detection Classification framework using Fast and Mask Deep learning. In 2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-6). IEEE.

[23] Kumar, A., Janakirani, M., Anand, M., Sharma, S., Vivekanand, C. V., & Chakravarti, A. (2022). Comparative Performance Study of Difference Differential Amplifier Using 7 nm and 14 nm FinFET Technologies and Carbon Nanotube FET. Journal of Nanomaterials, 2022.

[24] Vijetha, T., Mallick, P. S., Karthik, R., & Rajan, K. (2022). Effect of Scattering Angle in Electron Transport of AlGaN and InGaN. Advances in Materials Science and Engineering, 2022.

[25] Kumar, H., Prasad, R., Kumar, P., & Hailu, S. A. (2022). Friction and Wear Response of Friction Stir Processed Cu/ZrO 2 Surface Nano-Composite. Journal of Nanomaterials, 2022.

[26] Bhanuprakash, Lokasani, Soney Varghese, and Sitesh Kumar Singh. "Glass Fibre Reinforced Epoxy Composites Modified with Graphene Nanofillers: Electrical Characterization." Journal of Nanomaterials (2022).

[27] Jangam, N. R., Guthikinda, L., & Ramesh, G. P. (2022). Design and Analysis of New Ultra Low Power CMOS Based Flip-Flop Approaches. In Distributed Computing and Optimization Techniques: Select Proceedings of ICDCOT 2021 (pp. 295-302). Singapore: Springer Nature Singapore.

[28] Chandrasekaran, S., Satyanarayana Gupta, M., Jangid, S., Loganathan, K., Deepa, B., & Chaudhary, D. K. (2022). Unsteady radiative Maxwell fluid flow over an expanding sheet with sodium alginate water-based copper-graphene oxide hybrid nanomaterial: an application to solar aircraft. Advances in Materials Science and Engineering, 2022.

[29] Shareef, S. K., Sridevi, R., Raju, V. R., & Rao, K. S. (2022). An Intelligent Secure Monitoring Phase in Blockchain Framework for Large Transaction. IJEER, 10(3), 536-543.

[30] Koppula, N., Rao, K. S., Nabi, S. A., & Balaram, A. (2023). A novel optimized recurrent network-based automatic system for speech emotion identification. Wireless Personal Communications, 128(3), 2217-2243.

[31] Ali, F., Kumar, T. A., Loganathan, K., Reddy, C. S., Pasha, A. A., Rahman, M. M., & Al-Farhany, K. (2023). Irreversibility analysis of cross fluid past a stretchable vertical sheet with mixture of Carboxymethyl cellulose water based hybrid nanofluid. Alexandria Engineering Journal, 64, 107-118.

[32] Pittala, C. S., Vijay, V., & Reddy, B. N. K. (2022). 1-Bit FinFET carry cells for low voltage high-speed digital signal processing applications. Silicon, 1-12.

[33] Saran, O. S., Reddy, A. P., Chaturya, L., & Kumar, M. P. (2022). 3D printing of composite materials: A short review. Materials Today: Proceedings.

[34] Dasari, K., Anjaneyulu, L., & Nadimikeri, J. (2022). Application of C-band sentinel-1A SAR data as proxies for detecting oil spills of Chennai, East Coast of India. Marine Pollution Bulletin, 174, 113182.

[35] Rao, A. D., Chaitanya, A. K., Seshaiah, T., & Bridjesh, P. (2022). An Integrated Approach by Using Various Approaches for a Green Supplier Selection Problem. In Recent Advances in Manufacturing, Automation, Design and Energy Technologies: Proceedings from ICoFT 2020 (pp. 909-919). Springer Singapore.

[36] Yakaiah, P., & Naveen, K. (2022). An Approach for Ultrasound Image Enhancement Using Deep Convolutional Neural Network. In Advanced Techniques for IoT Applications: Proceedings of EAIT 2020 (pp. 86-92). Springer Singapore.

[37] Kumar, C. A., & Haribabu, K. (2022). A Great Adaptive SNR Assumed Low Power LDPC Decoder. In Advanced Techniques for IoT Applications: Proceedings of EAIT 2020 (pp. 443-451). Springer Singapore.

[38] Thottempudi, P., Dasari, V. S. C. B., & Sista, V. S. P. (2022). Recognition of Moving Human Targets by Through the Wall Imaging RADAR Using RAMA and SIA Algorithms. In Advanced Techniques for IoT Applications: Proceedings of EAIT 2020 (pp. 544-563). Springer Singapore.

[39] Arun, V., Reddy, D. L., & Rao, K. N. (2022). A Novel Analysis of Efficient Energy Architecture in Cryptography. In Advanced Techniques for IoT Applications: Proceedings of EAIT 2020 (pp. 339-345). Springer Singapore.

[40] Amareswer, E., & Raju Naik, M. (2022). Smart Erobern of Vehicles on Crosswalks. In Advanced Techniques for IoT Applications: Proceedings of EAIT 2020 (pp. 489-497). Springer Singapore.