Original Article

Analysis of Novel Machine learning algorithms for improved services in smart health care applications

Dr D Anitha[1], Dr. N. Bindu Madhavi[2], V Siva Prasad[3], P. Neelima[4], Karthick. S[5]

[1]Assistant Professor, Department of ECE, GITAM University, Hyderabad, TS, India.

[2]Associate Professor, Management Programmes, Centre for Distance & Online Education, Koneru Lakshmaiah Education Foundation, (Deemed to be University), Vaddeswaram, AP, India.

[3]Assistant Professor, Department of CSE, Sree Vidyanikethan Engineering college Autonomous), Tirupati, AP, India.

[4]Assistant Professor, Department of Computer Science and Engineering, Sri Padmavati Mahila Visvavidyalayam, Tirupati, AP, India.

[5]Assistant Professor, Department of CSE, SRMIST Delhi NCR Campus, Ghaziabad, India

Email: adid@gitam.edu

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Abstract

Artificial intelligence (AI) and machine learning (ML) will be increasingly used in healthcare because to the increasing complexity and volume of data in the industry. Payers, providers, and organizations in the life sciences are already using various forms of AI and ML. Diagnosis and treatment suggestions, patient participation and adherence, and management tasks are the main types of applications. These health monitors can keep tabs on a person's emotional and physical well-being. Numerous medical and psychological conditions can be traced back to stress, anxiety, and high blood pressure. Conditions associated with advancing age demand special consideration here, including stress, anxiety, and hypertension. Early detection of health issues through monitoring of stress, worry, and blood pressure is key to avoiding irreversible harm. This will improve people's lives by decreasing stress and medical expenses. Using covert wearable sensors & machine learning methods, develop innovative technological solutions for continuous monitoring of stress, worry, and blood pressure. This study proposes the development of an intelligent healthcare system that makes use of AI and ML in order to effectively address problems in the healthcare sector and to facilitate the optimization of care plans for individual patients. The suggested AI & ML -assisted method shows its ability to aid a patient admitted to the hospital via emergency medical services by quickly processing the patient's data and providing opportunities for early diagnosis of life-threatening illnesses. It can analyze comprehensive human genomic data & genetics in the clinic, automatically recognize complex patterns collected from radiologists, and provide radiologist reports, laboratory reports, and a plethora of other decision-support tools to aid clinicians.

Keywords: Artificial intelligence, smart healthcare, Machine learning.

1. INTRODUCTION

The concept of "Smart Health" emerged as an offshoot of "Smart Cities" and "Electronic Health Records" (e-Health) Definition: "cities strongly established on information and communications technology that invest in social and human capital to enhance the quality of life of their residents by encouraging economic growth, offer, wise use of resources, sustainable development, and efficient mobility while guaranteeing the security and privacy of the citizens." "an developing field at the crossroads of health informatics, public health, and business," e-Health refers to health information and services that are provided, or improved, via the Internet and other associated technologies. Broadly speaking, the term "health IT" refers to "the use of information and communication technologies to enhance health care on a local, regional, and global scale." It's important to note the overlap among s-Health & Mobile Health (m-Health), which is described as "developing communications technology and networking devices for healthcare systems."

The discipline of Machine Learning (ML) emerged from AI (AI). Evolving computer behavior in response to empirical data is the focus of this field of study, which involves the design and development of algorithms. Rapid advancements in the ML methodology can be attributed to several factors: advancements in ML algorithms, improved data collection techniques, more robust and reliable computer networks, the introduction of novel sensors/IO units, and a growing focus on adapting to users' individual preferences. It is clear that ML plays a significant role in s-Health, with the potential to enhance the standard of care provided by healthcare providers through more precise medical diagnosis, early disease prediction, and disease analyses[17].

Large numbers of heterogeneous devices, dispersed throughout the network, generate a steady flow of data in IoT systems [1]. For the most part, we use a five-step workflow model consisting of question formulation, data collection, data processing, data visualization, and evaluation to plan out our IoT app designs. Although mining IoT data for previously undiscovered information and insights holds great promise for enhancing our quality of life, doing so is a challenging task that cannot be accomplished using conventional methods [2]. In fact, with the advent of IoT devices, AI has been tried to introduce that uses constant monitoring to aid in illness diagnosis, alerting caregivers or physicians as needed. In addition, a decision - making support system can be implemented using these devices to aid in the selection process (DSS). The shift from a manual, unpleasant, and moment process to an intelligent, computerized, and time-efficient one is a major benefit of the new system. Further, there have been instances where doctors were unable to provide adequate treatment for patients due to a lack of knowledge about critical circumstances, leading to poor decisions and even patient deaths. Machine learning (ML) & deep learning (DL) methods are two of the most common types of AI algorithms used to train these robots [3][19]. In recent years, DL has seen extensive use in a variety of IoT applications [4]. Part of the machine learning field (ML), it requires a lot of processing power and money to implement. Integrating DL methods into IoT to boost application performance is a challenge. For the future generation of IoT networks, it is essential to combine these methodologies while striking a balance between computational cost and efficiency [2][18].

Because of its impressive results in areas such as image identification, retrieval of information, speech recognition, language processing, urban localization, and physiological and psychological condition detection, deep learning (DL) will play a crucial role in the development of a smarter IoT. In addition, these services provide the framework for IoT programs. Actually, DL has been widely used in numerous IoT applications over the past decade [4,5]. Figure 1 depicts the various parts that make up smart healthcare[20].

As a new sector of e-Health, Smart Health seeks to improve patient care by integrating data from smart city infrastructure with electronic health records (EHR). When it comes to providing emergency service and pagers for doctors, nurses, and technicians, the concept of a "smart health system" is that it uses all data from sensors on the patient's body, home automation, smart city infrastructure, & robots to help to make better decisions and enhance healthcare (see Fig. 1). As an added bonus, it can help with things like self-diagnosis, monitoring, early detection, and treatment. Data acquisition, networking & computing technologies, security and privacy, data analysis, and data dissemination are all components of the smart health system's data pipeline[21].

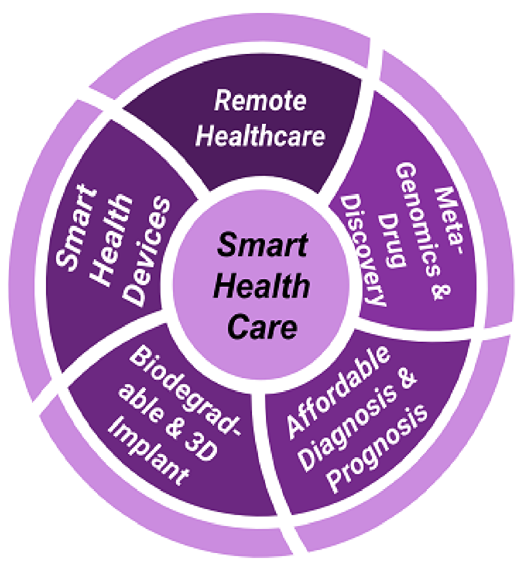

Figure 1. Components of Smart Health Care

2. Literature Survey:

The benefits of remote health monitoring in many settings have been demonstrated by research in related domains, however this may not be the most essential aspect of the topic. Hospital resources like doctors and beds could be less stressed if non-critical patients could be monitored remotely at home. It could help the elderly remain in their own homes for longer or improve healthcare access for individuals in rural locations. Simply put, it has the potential to make people more in charge of their own health while also easing the burden on healthcare institutions[22].

As a matter of fact, there are hardly any drawbacks to remote health monitoring. Major drawbacks include the potential for data breaches due to the centralization of sensitive information, the need for periodic recalibration of sensors to ensure accurate monitoring, and the potential for disconnection from health care if the patient is out of cell membrane range or one‘s devices run out of battery. The good news is that all of these problems have been tackled before and are being discussed in the literature throughout the rest of this paper. As the drawbacks are mitigated, IoT-based solutions for remote health surveillance offer a promising option for meeting the growing need for medical care in the coming years[23][25].

Many researchers have focused on the problem of recovery from physical trauma. In [6], we find a method that, given a patient's symptoms, may produce a personalized rehabilitation program. This is accomplished by matching the patient's symptoms, diseases, and treatments against a database of those experienced by prior patients. A physician must enter patient symptoms and approve the proposed treatment plan, although in 92.3% of instances, the physician agreed with the system's assessment and made no changes to the treatment plan. In the meantime, in [7], mathematical models are proposed for measuring angular position in physical hydrotherapy systems. This will allow progress in joint mobility to be monitored as treatment progresses[24].

In [6], the efficacy of current Internet of Things technologies in a system to monitor Parkinson's disease patients is assessed. Their research suggests that vision-based technologies (such as webcams) in the home might be used in tandem with wearable sensors for detecting movement patterns, tremors, and overall activity levels to track the development of Parkinson's Disease. The authors also note that machine learning has the potential to improve future treatment strategies. In [8], a method was proposed for the accurate monitoring of blood glucose in diabetic patients' blood. Patients must manually obtain blood-glucose levels at predetermined intervals with this method. After that, it takes into account two distinct types of glucose imbalance. Both high or low blood sugar and a missed blood sugar reading are causes for concern. The system then determines whether to alert the patient, their caretakers, or emergency medical personnel, such as doctors, based on the extent of the anomaly detected. Although this method has been demonstrated to be feasible, it might be enhanced by incorporating automated blood-glucose measurements [27].

In [9], a system was constructed to detect cardiac arrests using off-the-shelf parts and a specialized antenna. The heart's electrical activity is measured by an electrocardiogram (ECG) sensor and analyzed by a microcontroller. It then transmits that data wirelessly over Bluetooth to the user's smartphone, where the Electrocardiogram data is processed and displayed via an app. The authors note that it would be preferable to have software that could foresee cardiac attacks. Measurement of respiratory rate, which has been shown to aid inside the prediction of a heart attack [10], could lead to further enhancements [26].

Several needs for the development of such healthcare systems become clear after examining this diverse set of existing Internet - of - things health systems. All of these articles highlight the importance of sensor technology in health monitoring. All three emphasize the importance of wireless, externally-worn sensors as a key component of their systems. Environment or vision-based sensors are also recommended for usage in and around the house in a number of studies [11, 12]. As a result, the system can only be used in a single place. All necessary sensors should ideally be implemented as tiny, portable, externally worn nodes. This would give people a convenient and painless way to track their health from any location. Patients might be more open to embracing health monitoring technologies if it didn't require them to get surgically implanted sensors or cameras. In addition, unlike implanted sensors or eyesight home sensors, externally wearing nodes might be easily repaired or replaced [28].

The importance of communications for an IoT healthcare system has been highlighted by already existing systems. A number of the current system concepts [8, 12, 9] propose using Bluetooth or another kind of short-range communication to send sensor data to a smartphone for analysis. The processed data can subsequently be sent from the client to the healthcare practitioner, generally a doctor, via short message service (SMS) or the Internet using long-range communication such as LTE. The most significant drawback is that mobile phones have short battery lives and need to be recharged frequently; a person with a dead phone would be cut off from their healthcare team. To better manage healthcare data, a low-power node built for that purpose would be ideal [29][30][31].

A big data healthcare system needs cloud storage that can accommodate large amounts of data with various structures, as demonstrated by a number of earlier publications [13, 14, 15]. A short pulse sensor worn by a thousand people and communicating with an online storage database once an hour through an LPWAN would generate 168,000 data points every week. As more individuals begin using wearable sensors that sync with the cloud infrastructure, and as new types of sensors enter the market, this figure rises dramatically [32[33]. Algorithms for machine learning can be deployed in the cloud's high-computing environment to make use of the massive amounts of data that will be generated and stored there. These algorithms might be programmed to do a wide range of tasks, including data mining, trend identification, diagnosis, and treatment planning[35].

3. Methodology:

In this section, we offer a new framework Hidden Privacy that can automatically discover and clean medical entities from medical records (such as sensor data, reports, and medication prescriptions). Since these records contain sensitive information about patients, they must be cleaned before being printed or transmitted. As a result, strategies focused on sanitization were presented [16]. Sanitization is replacing the most sensitive and worrying terminology with less specific ones. As a result, patients' right to privacy over their unstructured medical data may be protected from intrusions and other risks . we can see how the suggested architecture of a fog-enabled Hidden Security framework is separated into four distinct phases. Furthermore, the general flow of the suggested scheme is depicted in the activity diagram Figure 2[17]. We now delve into the inner workings of the suggested model (and its several layers).

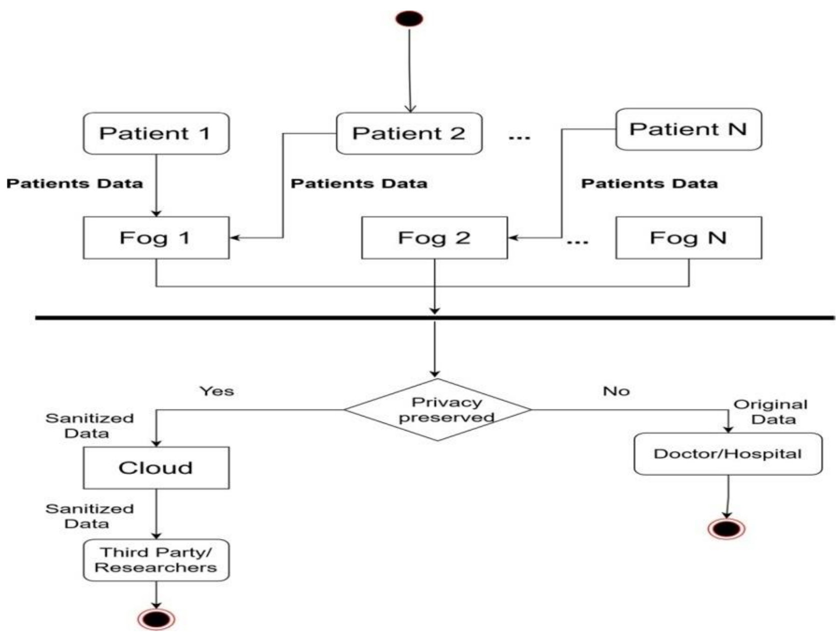

Figure 2. Proposed Smart Health Care Framework

Figure 3. Proposed Layers in smart Health Care

(i) Application layer : Consumers of the medical information collected by the sensors are the focus of this layer. Users can include medical professionals, ancillary personnel, the patient, and the patient's loved ones. This layer also includes outside actors, such as various research institutions. In contrast to the rest of the customers, who access the cloud's raw data, those in the fog layer only have access to data that has been cleaned.

(ii) Cloud layer : The cloud layer stores information that has been scrubbed of personally identifiable details by the fog layer. Data stored in the cloud may be requested by third parties like academic institutions, publishing houses, and pharmaceutical companies..

(iii) Fog layer: Real-time applications that cannot afford even a second of delay (like those used in medical crises) benefit greatly from the introduction of the fog layer because it helps to lower power consumption and prevent backhaul congestion [33]. Medical record recognition and patient confidentiality are handled by the control layer, the fog. As can be seen in Fig. 3, it consists of two primary modules: I a module called MER for recognizing unstructured data, and ii) a module called r-sanitized for cleaning up that data. Shows how potentially sensitive phrases are further cleaned up in the fog layer before being sent to the cloud. Researchers from other institutions have access to this cleansed data in the cloud.

Summaries of information obtained from the network level are provided in reports. On this layer, prescriptions written by doctors are temporarily stored. To conserve bandwidth and reduce latency, only the summaries are sent to the cloud before the whole data set is sent. Both reporters covering the medical field and patients themselves will benefit from having direct access to such data, since it will allow them to receive answers from the fog in real time. Before being uploaded to the cloud, the data is cleansed. After this is done, the cleaned data can be given to other researchers. The Deep Privacy method protects this information. Let's pretend that anything happens to the data when it's being transferred from the fog to the cloud. Thus, the adversary will be unable to access the original, unfiltered data. The study does not address the security of information during transit from the network level to the fog. The data sensed by a gadget and its subsequent transfer to the fog nodes were thought to be safe.

4. Evaluation:

We just use n2c2-2010 data-set [18] designed for extracting medical concepts, such as health records, current medications, and test results, in our simulations. A combination of the Precision, Recall, and F-score Metrics is used for the analysis. The keras [19] built-in package in Python is used to construct the recognition system for the unstructured medical data. Here are the findings from the analysis is shown in table 1:

Table 1. Evaluation Results of Various Algorithms

Name of the Algorithm	**Precision**	**Recall**	**F-Score**
LSTM	87.5	82.6	86.3
LSTM+CRF	89.3	86.2	89.45
Proposed(LSTM+CNN+CRF)	92.6	95.6	93.52

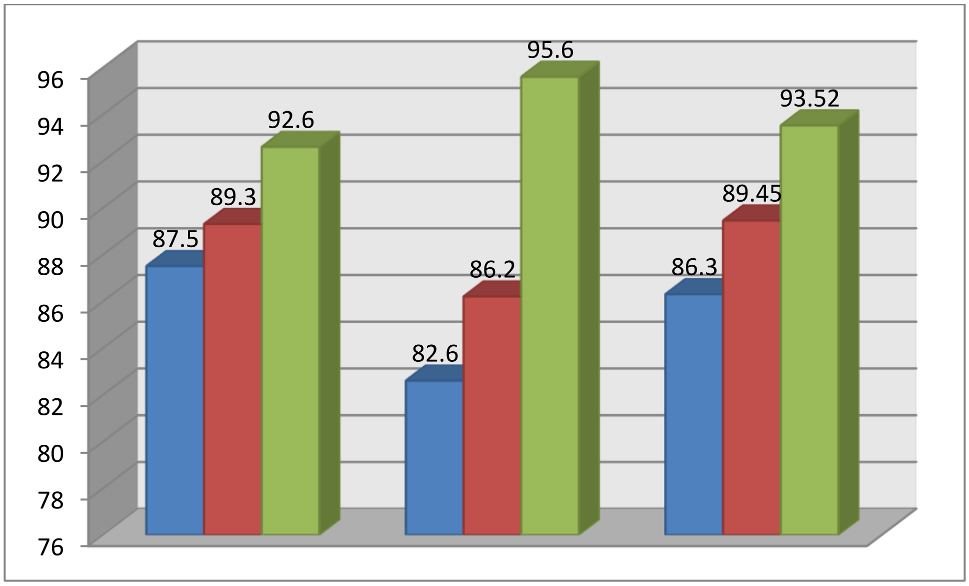

Figure 4. Evaluation Results of our proposed System

The above figure 4 represents the comparison of three algorithms and the evaluated results of three algorithms in terms of Precision, Recall and F-score Metrics. When compared to all the algorithms our proposed algorithm which is a combination of CNN+LSTM+CRF will performs ahead. The precision Precision, Recall and F-score Metrics are 92.6%,95.6% and 93.52% which is 5% better compared to second algorithm and 9% better compared to the first algorithm.

5. Conclusion:

Smart healthcare is a rapidly growing and extremely important area of study that has the potential to have a significant impact on the established healthcare system. The presented architecture demonstrates that this ML-based approach to healthcare cost reduction and stakeholder management may be implemented by any healthcare organization. When a patient is admitted to the hospital via emergency medical services, the suggested ML-assisted system is there to help them through the entire process, from processing their long data to detecting serious diseases to automatically recognizing complex patterns to analyzing their entire molecular data and genetic makeup. In smart healthcare infrastructures, the advent of fog computing offers a viable solution at the network's edge in terms of latency. It has the potential to improve current medical research, aid in disease diagnosis, and provide answers to future problems in the medical industry. Before giving patients' private medical records to researchers, it's crucial to take measures to protect their anonymity. However, recent research reveals privacy infractions and lower data use due to sloppy handling of consumption and privacy issues.

REFERENCES

1. Ma, X.; Yao, T.; Hu, M.; Dong, Y.; Liu, W.; Wang, F.; Liu, J. A survey on deep learning empowered IoT applications. IEEE Access 2019, 7, 181721–181732
2. Zikria, Y.B.; Afzal, M.K.; Kim, S.W.; Marin, A.; Guizani, M. Deep learning for intelligent IoT: Opportunities, Challenges and Solutions. Comput. Commun. 2020, 164, 50–53
3. Durga, S.; Nag, R.; Daniel, E. Survey on machine learning and deep learning algorithms used in internet of things (IoT) healthcare. In Proceedings of the 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 27–29 March 2020; pp. 1018–1022.
4. Saleem, T.J.; Chishti, M.A. Deep learning for Internet of Things data analytics. Procedia Comput. Sci. 2020, 163, 381–390.
5. Keikhosrokiani, P. IoT for enhanced decision-making in medical information systems: A systematic review. In Enhanced Telemedicine and e-Health; Springer: Cham, Switzerland, 2021; pp. 119–140.
6. Y. J. Fan, Y. H. Yin, L. D. Xu, Y. Zeng, and F. Wu, "IoT- based smart rehabilitation system," IEEE Transactions on Industrial Informatics, vol. 10, no. 2, pp. 1568–1577, 2019.
7. Ganesh, D., et al. "Implementation of AI Pop Bots and its allied Applications for Designing Efficient Curriculum in Early Childhood Education." International Journal of Early Childhood 14.03: 2022.
8. Kumar, M. Sunil, et al. "Deep Convolution Neural Network Based solution for Detecting Plant Diseases." Journal of Pharmaceutical Negative Results

(2022): 464-471.
9. P. Sai Kiran. "Power aware virtual machine placement in IaaS cloud using discrete firefly algorithm." Applied Nanoscience (2022): 1-9.
10. Kumar, T. P., & Kumar, M. S. (2021). Optimised Levenshtein centroid cross-layer defence for multi-hop cognitive radio networks. IET Communications, 15(2), 245-256.
11. Natarajan, V. Anantha, et al. "Segmentation of nuclei in histopathology images using fully convolutional deep neural architecture." 2020 International Conference on computing and information technology (ICCIT-1441). IEEE, 2020.
12. Sangamithra, B., P. Neelima, and M. Sunil Kumar. "A memetic algorithm for multi objective vehicle routing problem with time windows." 2017 IEEE International Conference on Electrical, Instrumentation and Communication Engineering (ICEICE). IEEE, 2017.
13. Sunil Kumar, M., and A. Rama Mohan Reddy. "An Efficient Approach for Evolution of Functional Requirements to Improve the Quality of Software Architecture." Artificial Intelligence and Evolutionary Computations in Engineering Systems. Springer, New Delhi, 2016. 775-792.
14. R. C. A. Alves, L. B. Gabriel, B. T. d. Oliveira, C. B. Margi, and F. C. L. d. Santos, "Assisting Physical (Hy- dro)Therapy With Wireless Sensors Networks," IEEE Internet of Things Journal, vol. 2, no. 2, pp. 113–120, 2020.
15. S. H. Chang, R. D. Chiang, S. J. Wu, and W. T. Chang, "A Context-Aware, Interactive M-Health System for Diabetics," IT Professional, vol. 18, no. 3, pp. 14–22, 2018.
16. G. Wolgast, C. Ehrenborg, A. Israelsson, J. Helander,E. Johansson, and H. Manefjord, "Wireless Body Area Network for Heart Attack Detection [Education Corner]," IEEE Antennas and Propagation Magazine, vol. 58, no. 5, pp. 84–92, 2019.
17. M. A. Cretikos, R. Bellomo, K. Hillman, J. Chen,S. Finfer, and A. Flabouris, "Respiratory rate: the ne- glected vital sign," The Medical Journal of Australia, vol. 188, pp. 657–659, 2018.
18. N. Zhu, T. Diethe, M. Camplani, L. Tao, A. Burrows, N. Twomey, D. Kaleshi, M. Mirmehdi, P. Flach, and Craddock, "Bridging e-Health and the Internet of Things: The SPHERE Project," IEEE Intelligent Sys- tems, vol. 30, no. 4, pp. 39–46, 2019.
19. C. F. Pasluosta, H. Gassner, J. Winkler, J. Klucken, and B. M. Eskofier, "An emerging era in the management of Parkinson's disease: Wearable technologies and the internet of things," IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 6, pp. 1873–1881, 2018.
20. Sangamithra, B., Manjunath Swamy, B.E., Sunil Kumar, M. (2022). Personalized Ranking Mechanism Using Yandex Dataset on Machine Learning Approaches. In: Kumar, A., Ghinea, G., Merugu, S., Hashimoto, T. (eds) Proceedings of the International Conference on Cognitive and Intelligent Computing. Cognitive Science and Technology. Springer, Singapore. https://doi.org/10.1007/978-981-19-2350-0_61
21. Kumar, M. S., Siddardha, B., Reddy, A. H., Reddy, C. V. S., Shaik, A. B., & Ganesh, D. (2022). APPLYING THE MODULAR ENCRYPTION STANDARD TO MOBILE CLOUD COMPUTING TO IMPROVE THE SAFETY OF HEALTH DATA. Journal of Pharmaceutical Negative Results, 1911-1917.
22. Burada, S., Swamy, B. E., & Kumar, M. S. (2022). Computer-Aided Diagnosis Mechanism for Melanoma Skin Cancer Detection Using Radial Basis Function Network. In Proceedings of the International Conference on Cognitive and Intelligent Computing (pp. 619-628). Springer, Singapore.
23. Prasad, T. G., Turukmane, A. V., Kumar, M. S., Madhavi, N. B., Sushama, C., & Neelima, P. (2022). CNN BASED PATHWAY CONTROL TO PREVENT COVID SPREAD USING FACE MASK AND BODY TEMPERATURE DETECTION. Journal of Pharmaceutical Negative Results, 1374-1381.
24. AnanthaNatarajan, V., M. Sunil Kumar, and V. Tamizhazhagan. "Forecasting of Wind Power using LSTM Recurrent Neural Network." Journal of Green Engineering 10 (2020).
25. Natarajan, V. A., Kumar, M. S., Tamizhazhagan, V., & Chevdumoi, R. M. (2022). PREDICTION OF SOIL PH FROM REMOTE SENSING DATA USING GRADIENT BOOSTED REGRESSION ANALYSIS. Journal of Pharmaceutical Negative Results, 29-36.
26. Natarajan, V. Anantha, M. Sunil Kumar, Rizwan Patan, Suresh Kallam, and Mohamed Yasin Noor Mohamed. "Segmentation of nuclei in histopathology images using fully convolutional deep neural architecture." In 2020 International Conference on computing and information technology (ICCIT-1441), pp. 1-7. IEEE, 2020.
27. Sreedhar, B., BE, M. S., & Kumar, M. S. (2020, October). A comparative study of melanoma skin cancer detection in traditional and current image processing techniques. In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 654-658). IEEE.
28. Natarajan, MS Kumar V. Anantha, and D. Ganesh Macha Babitha. "Machine Learning Based Identification of Covid-19 From Lung Segmented CT Images Using Radiomics Features." Biosc. Biotech. Res. Comm. Special Issue 14.07: 350-355.
29. Y. YIN, Y. Zeng, X. Chen, and Y. Fan, "The internet of things in healthcare: An overview," Journal of Industrial Information Integration, vol. 1, pp. 3–13, 3 2019.
30. D. V. Dimitrov, "Medical Internet of Things and Big Data in Healthcare," Healthcare Informatics Research, vol. 22, no. 3, pp. 156–163, 7 2019.
31. B. Xu, L. D. Xu, H. Cai, C. Xie, J. Hu, and F. Bu, "Ubiquitous Data Accessing Method in IoT-Based In- formation System for Emergency Medical Services," IEEE Transactions on Industrial Informatics, vol. 10, no. 2, pp. 1578–1586, 2019.
32. Iwendi, C., Moqurrab, S. A., Anjum, A., Khan, S., Mohan, S., & Srivastava, G. (2020). N-sani- tization: A semantic privacy-preserving framework for unstructured medical datasets. Computer Communications.
33. Moqurrab, S.A., Tariq, N., Anjum, A. et al. A Deep Learning-Based Privacy-Preserving Model for Smart Healthcare in Internet of Medical Things Using Fog Computing. Wireless Pers Commun 126, 2379–2401 (2022).
34. Uzuner, Ö., South, B. R., Shen, S., & DuVall, S. L. (2011). 2010 i2b2/va challenge on concepts, asser- tions, and relations in clinical text. Journal of the American Medical Informatics Association, 18(5), 552–556.
35. Chollet, F. et al. (2015). Keras. https://github.com/fchollet/keras