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Optimizing Healthcare in the Digital Era: Fusion of IoT with other Techniques

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Abstract

The Internet of Things (IoT) has helped explore the healthcare industry. The present paper discusses the benefits and challenges associated with IoT in healthcare, highlights notable use cases, and presents the future prospects and considerations for successful implementation. Through a comprehensive examination of the topic, this paper aims to provide insights into the role of IoT in enhancing healthcare delivery, improving patient outcomes, and transforming the healthcare domain. A case study of brain tumor classification is investigated to explore IoT's applicability in healthcare. The VGG 16 model improved more consistently over the epoch, achieving higher validation accuracy than other models. In contrast, the discrepancies in validation accuracy and loss indicate the degree of variability of these models. The concept is augmented with fuzzy logic, nearness monitoring, and IoT in healthcare to understand future applicability, promising a better perspective on their transformational prowess.

Keywords: Internet of Things, E-Health, Personalized Medicine, Artificial Intelligence

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1. Introduction

In an era of technological evolution, healthcare has been irrevocably altered, transforming through IoT. This present article helps to understand IoT's essence within healthcare, profoundly impacting patient treatment in increasingly digital epoch.

Confronted with escalating costs, the specter of patient safety, this article fine-tunes patient care and gives a streamlined workflow, culminating in augmented outcomes. The advent of IoT in healthcare marks a pivotal shift in patient care paradigms, as seen in [1, 2], which gives the current integration of IoT within healthcare settings, presenting a new domain of connectivity and patient engagement [3] further expand in this domain, demonstrating the extensive capabilities of IoT applications that promise to revolutionize not only healthcare but also intersecting sectors such as agriculture and urban development. Moreover, Rodić et al. [4] studied the user-centric perspective, examining the increasing intention to adopt IoT-based healthcare technologies in rehabilitation. This identifies a broader acceptance and augmentation of these technologies in patient-centric care. Offering real-time, remote monitoring of patients are the major transformations recorded by IOT. It's a vigilant eye over vital signs, medication regimes, and disease progression monitoring. Beyond monitoring, IoT is a conduit for medical data flow, bridging healthcare entities and fostering a unified front in patient care. Yet, this data is often cloaked in shades of uncertainty—here, the role of fuzzy logic is of utmost importance. This synergy of IoT

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with fuzzy logic's handling uncertainity may give more tailored, dynamic patient care, a leap towards the future of health. In the IoT system, the notion of 'nearness' takes on a pivotal role, especially when framed within the confines of healthcare. Envision IoT devices, having acute sensitivity of proximity sensors, becoming indispensable in the healthcare sector. These devices are not mere trackers but a life saviours, measuring the delicate understanding of distances with precision.

As the world discusses social distancing and infection mitigation, the vigilance of IoT in monitoring distance measure/proximity becomes a tool of understanding. These intelligent systems serve as points, ensuring that the distance that is crucial for understanding the spread of disease act as an essential parameter that bind individuals within healthcare are neither too entangled nor too stretched, maintaining a balance that is critical and accurate for calculations. The concepts of nearness in computing [5], fuzzy nearness [6, 7], and nearness and image processing [8] have great importance in the area where distance is considered. This paves the way for future researches that is an amalgamation of mathematical concepts with IOT.

2. IoT in Healthcare

IoT refers to a vast network of interconnected devices, objects, and sensors that collect and exchange data through the internet. In IoT, physical objects are embedded with sensors, software, and network connectivity, enabling them to gather and transmit data. These objects range from everyday items, such as wearables, medical devices, and appliances, to industrial equipment and infrastructure. The following Figure 1 represents the key components of the devices.

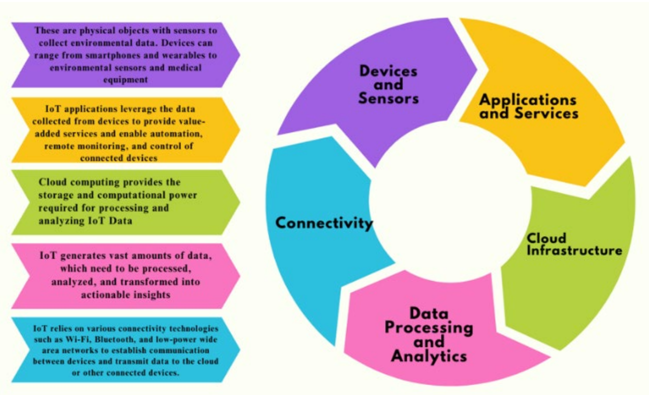

Figure 1. Key components of IOT devices

In Healthcare, IoT offers a range of characteristics and capabilities that have the potential to revolutionize patient care as shown in Figure 2.

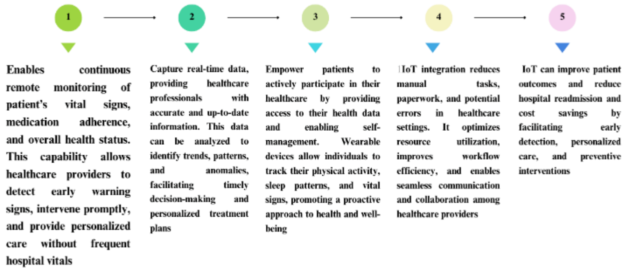

Figure 2. Key Characteristics of IoT in Healthcare

The IoT ecosystem comprises interconnected devices, connectivity technologies, data processing capabilities, cloud infrastructure, and applications/services. In healthcare, IoT's Characteristics, and capabilities, such as remote patient monitoring, real-time data analysis, enhanced patient engagement, streamlined workflows, etc, have immense potential to transform how healthcare is delivered and experienced.

3. Uses Cases of IoT in Healthcare

3.1. Applications

1. Remote Patient Monitoring: IoT devices collect real-time patient data and send it to healthcare providers. This helps remotely monitor heart rate, blood pressure, and glucose levels, allowing healthcare professionals to track patients' health conditions without requiring them to be physically present [9]. Technavio has announced its latest market research report, as shown in Figure 3, Global Remote Patient Monitoring Market 2020-2024. As per the report, remote patient monitoring is poised to grow by USD 928.34 million during 2020-2024, progressing at a CAGR of almost 18% during the forecast period [10].

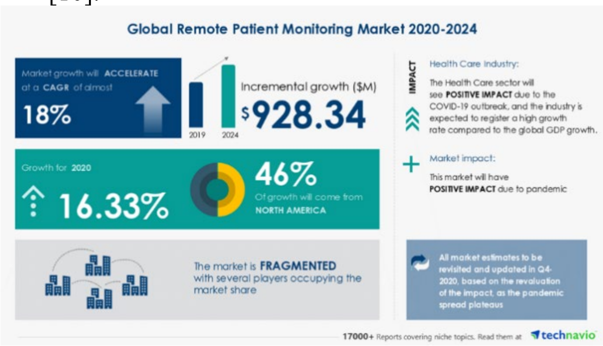

Figure 3. Analysis report matrix (Global Remote Patient Monitoring Market - Featuring Abbott Laboratories, Boston Scientific Corp., and General Electric Co. Among Others, 2020)

2. Smart Wearable Device: IoT-powered wearable devices like smartwatches, fitness trackers, and biosensors can monitor various health parameters and activities regularly. These devices can track steps, sleep patterns, heart rate, and calorie expenditure and detect falls or abnormal movements. The acquired data can be analyzed to provide insights into individuals' overall health and enable early health detection. The Figure 4, exhibited below, is an example of a wearable process [11].

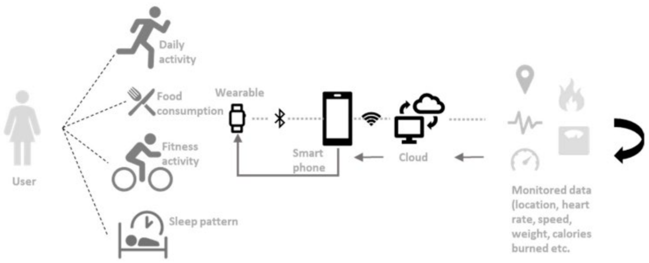

Figure 4. Example of a wearable process

3. Fall Detection and Prevention: IoT sensors in patients' homes or healthcare facilities can detect falls and trigger immediate alerts to caregivers or emergency services. These sensors can be embedded as wearable devices in flooring, furniture, etc [12]. They help prevent accidents, especially among elderly or vulnerable patients, by enabling quick response and assistance. The flow diagram for the wearable system's overall fall risk assessment is shown below in Figure 5 [13].

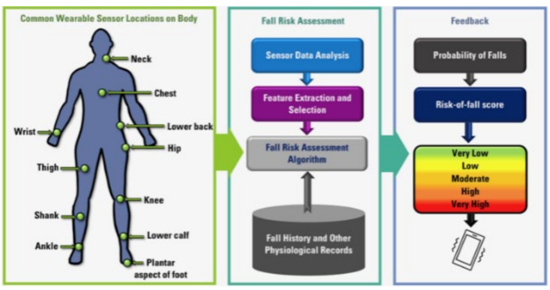

Figure 5. Flow diagram for the wearable system's overall fall risk assessment

4. Telemedicine and Virtual Consultations: IoT facilitates remote healthcare services through telemedicine platforms. Connected devices such as video conferencing tools, remote examination cameras, and diagnostic devices enable healthcare professionals to interact with patients virtually, diagnose illnesses, prescribe medications, and monitor progress remotely. This improves accessibility to healthcare, especially for patients in remote areas [14].
5. Hospital Workflow Optimization: IoT devices can enhance hospital operations by optimizing workflow efficiency. For example, IoT-enabled patient tracking systems can monitor patient flow, bed occupancy, and waiting times. This data can be analyzed to identify bottlenecks, streamline processes, and improve resource allocation, leading to better patient care and reduced wait times [15, 16].

Table 1 outlines the key characteristics and capabilities of IoT in healthcare and provides a brief explanation of how each aspect is achieved through IoT technologies.

Table 1. Key Characteristics and Capabilities of IoT in Healthcare

Aspect	Description	How
Remote Patient Monitoring	Continuous monitoring of vital signs, medication adherence, and health status in real-time.	Through wearable sensors and medical devices connected to cloud-based systems.
Real-Time Data Collection and Analysis	Capture of real-time data for accurate and up-to-date information, facilitating timely decision-making.	IoT devices collect and transmit data to cloud servers for analysis.
Enhanced Patient Engagement	Empowering patients with access to their health data through wearables and promoting proactive health management.	Wearable devices provide real-time health data to patients via mobile apps.
Streamlined Workflows and Efficiency	Automation of healthcare processes, resource optimization, improved workflows, and	IoT integration automates tasks and enhances communication among providers.

	enhanced collaboration among healthcare providers.	
Improved Outcomes and Cost Savings	Early detection, personalized care, preventive interventions, reduced hospital readmissions, and cost savings.	By analyzing data for early intervention and personalized treatments.

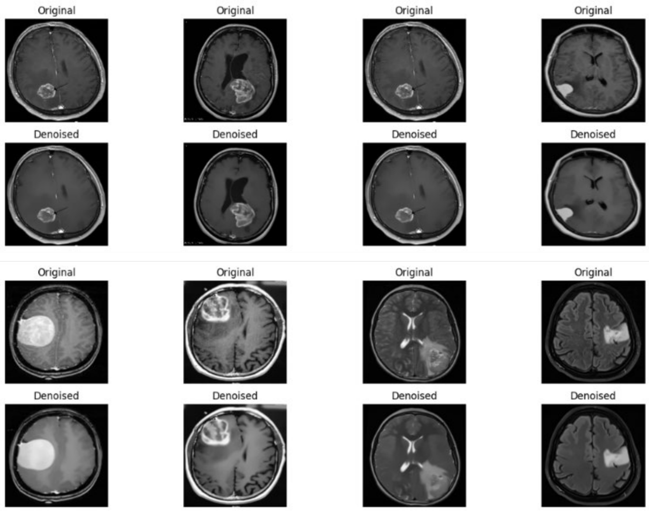

Figure 6. Sample images and the denoised images of the dataset

3.2. Case Study

In healthcare, integrating new technologies can potentially restructure the traditional healthcare system and its current challenges by intersecting medical imaging, artificial intelligence and IoT. In this section, a similar intersection of the above is endeavoured by considering a case study of brain tumour detection where the fusion of imaging techniques and state-of-the-art deep learning models are deployed to enhance diagnostic precision. This case study utilizes a comprehensive brain MRI image dataset that analyses the intricate details of neural structures and focuses on tumour identification.

Dataset Description

The data used in this case study is curated from the open-source repository [17] for the exploration and establishment of the use of IoT in healthcare using various data preprocessing techniques and the deployment of a sophisticated carted algorithm to classify the problem of normal and abnormal feasibility of brain tumours. This dataset comprises 253 high-resolution MRI scan images with various neuroimaging scenarios. The dataset is divided into two primary categories, with 88 MRI images depicting normal brain structures and 155 MRI images capturing instances of brain tumours, and this distribution ensures a balanced representation of this pathological condition.

The dataset underwent rigorous preprocessing within the Python Google Colab environment utilizing the cloud-based computing and classification of this dataset. Figure 6 exhibits a dataset snapshot illustrating original MRI images and their respective denoised counterparts generated using a Python-based preprocessing pipeline. Furthermore, the standardization and normalization of the dataset have also been catered to mitigate this problem effectively.

Model Architecture of VGG 16 [13]:

1. Input Layer:
- Input shape: (224, 224, 3) for images with dimensions 224x224 pixels and three color channels (RGB).
- No trainable parameters.
2. Feature Extraction (VGG16 Base Model):
- Several convolutional layers (block1_conv1, block1_conv2, ..., block5_conv3) for feature extraction.
- Each convolutional layer has learnable parameters (weights and biases) responsible for recognizing patterns in the input images.
3. MaxPooling Layers:
- MaxPooling2D layers (block1_pool, block2_pool, ..., block5_pool) reduce spatial dimensions and capture essential information.
- No trainable parameters in pooling layers.
4. Global Average Pooling Layer:
- The globalAveragePooling2D layer computes the average value for each feature map across all the spatial dimensions.
- Results in a 1D vector with 512 elements (one for each feature map).
5. Fully Connected Layers (Custom Head):
- Dense layers (dense_40, dense_41, dense_42) for further abstraction and learning complex patterns.
- The last dense layer (dense_43) outputs two classes (tumour and non-tumour) using softmax activation.
6. Total Parameters: 16,815,426
- The model has 16,815,426 parameters, representing the weights and biases of the convolutional and dense layers.
- This includes both trainable and non-trainable parameters.

7. Trainable Parameters: 2,100,738
- Out of the total parameters, 2,100,738 are trainable. These are the parameters that the model will adjust during training to learn from the data.

8. Non-trainable Parameters: 14,714,688
- Non-trainable parameters (often from pre-trained models) remain fixed during training. They represent the knowledge transferred from the ImageNet pre-training.

The detailed model summary is depicted in Figure 7 below.

```
Model: "model_22"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_20 (InputLayer)       [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 global_average_pooling2d_1  (None, 512)               0
 6 (GlobalAveragePooling2D)

 dense_70 (Dense)            (None, 1024)              525312

 dense_71 (Dense)            (None, 1024)              1049600

 dense_72 (Dense)            (None, 512)               524800

 dense_73 (Dense)            (None, 2)                 1026

=================================================================
Total params: 16815426 (64.15 MB)
Trainable params: 2100738 (8.01 MB)
Non-trainable params: 14714688 (56.13 MB)
_________________________________________________________________
```

Figure 7. Model summary of VGG16

Further, the VGG 16 model was deployed utilizing the Adam optimizer and the categorical cross entropy as the loss function with a total of 5 epochs in which its training, validation and loss were noted throughout the training period. During the first epoch, the training accuracy incepts was 43.66%, and validation accuracy was 68.42%, as depicted in the snippet from Python in Figure 8. Furthermore, it can also be seen that during the subsequent epoch, training accuracy enhanced and reached 88.70% by the fifth epoch, and the validation accuracy improved from 69.42% to 88.16% over a span of 5 epochs. Moreover, in the context of the loss function, which is responsible for measuring the difference between the predicted and the actual values, shows a consistent decrease from 7.8466 in the first epoch to 0.2931 in the 5th epoch. Similarly, for the cases of the validation set of analysis, the loss decreased from 0.5464 to 0.3289 over the five epochs. Based on the above results achieved, a plot of VGG 16 training and validation accuracy has been depicted in Figure 9 w.r.t to epoch.

```
Epoch 1/5
6/6 [==============================] - 3s 225ms/step - loss: 7.8466 - accuracy: 0.4633 - val_loss: 0.5464 - val_accuracy: 0.6842
Epoch 2/5
6/6 [==============================] - 1s 174ms/step - loss: 0.7711 - accuracy: 0.6949 - val_loss: 1.1249 - val_accuracy: 0.5526
Epoch 3/5
6/6 [==============================] - 1s 176ms/step - loss: 0.6932 - accuracy: 0.6949 - val_loss: 0.6118 - val_accuracy: 0.6711
Epoch 4/5
6/6 [==============================] - 1s 170ms/step - loss: 0.4212 - accuracy: 0.8305 - val_loss: 0.4229 - val_accuracy: 0.8026
Epoch 5/5
6/6 [==============================] - 1s 174ms/step - loss: 0.2931 - accuracy: 0.8870 - val_loss: 0.3289 - val_accuracy: 0.8816
```

Figure 8. Snippet of results from VGG16

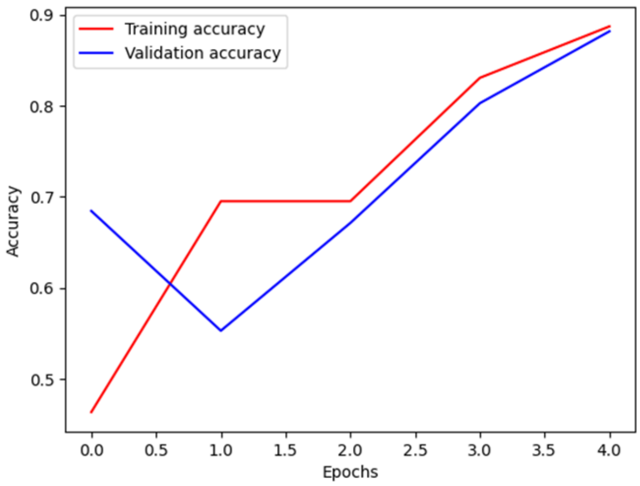

Figure 9. VGG16 training and validation accuracy

Furthermore, two other models, ResNet50 and MobileNetV2, have been deployed in this context to understand the behaviour of different models over VGG16 and come up with a comparison.

The ResNet50 model was also trained for the 5 number of epochs using the Adam optimizer and categorical cross entropy as the loss function, where the training accuracy started at 63.84%, whereas the validation accuracy was 40.79% in the first epoch. However, it has been found that the validation set did not show any significant improvement over the epoch, reaching 59.21% by the fifth epoch and performing worse compared to the VGG 16 model. Although the loss of the training decreased from 17.55 to 0.67 while validation loss increased from 10062.168 to 135070.59 as depicted in Figure 10 overall, this model was not able to surpass the VGG16 models in terms of loss improvement, training accuracy and validation accuracy.

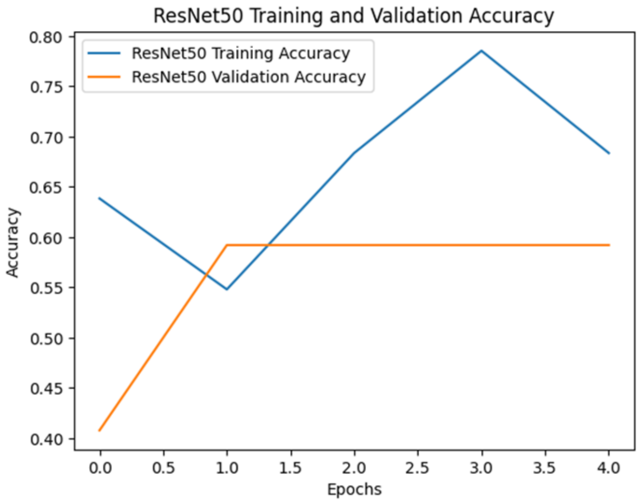

Figure 10. ResNet50 training and validation accuracy

On the other hand, another model, MobileNet V2, was also deployed over five epochs in a similar manner and training accuracy initiated at 63.84%, and the validation accuracy was 40.79% in the first epoch. The validation accuracy reached 59.21% over five epochs, and the loss on training set decreased from 19.88 to 0.42, while validation loss remained relatively high, proving that this model performed worst in comparison with VGG 16, as exhibited in Figure 11.

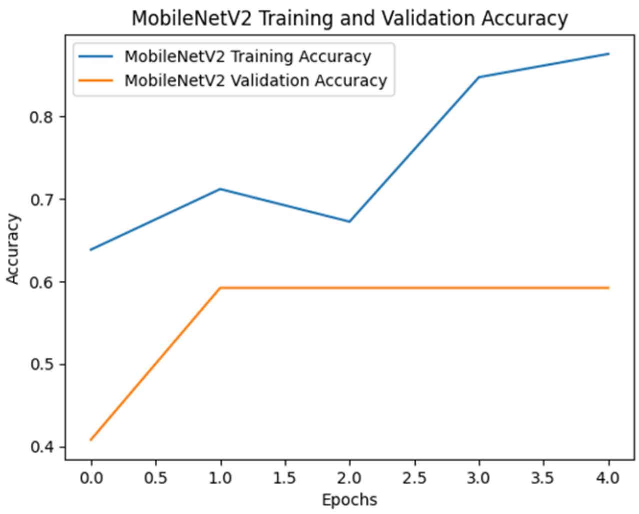

Figure 11. MobileNetV2 Training and validation accuracy

Overall, the ResNet50 and MobileNetv2 models showed terrible performance with minimal improvement in validation accuracy. The VGG 16 model demonstrated more consistent improvement over the epoch, achieving higher validation accuracy than other models, whereas the discrepancies in validation accuracy and loss indicate the degree of variability of these models. As a future scope further, this work can be enhanced for more epochs and then results can be more explored.

4. Integrating Fuzzy Logic And Nearness Monitoring With Iot In Healthcare

The integration of fuzzy logic, proximity, and IoT in healthcare represents a promising frontier in healthcare technology. As shown in Table 2, the concepts collectively help to improve patient assessment, safety, data analysis, patient engagement, workflow optimization, and diagnostics. Utilizing fuzzy logic helps to handle imprecise health data effectively, while amalgamation of nearness with IoT ensures patient safety and social distancing compliance. This integration can potentially help the healthcare domain by enhancing decision-making, patient care, and overall healthcare efficiency. The level of diagnosis, prediction of disease progression and the personalized treatment plans can be significantly improved utilizing large volumes of patient centric data collected through IOT devices and the integration of computational intelligence [18].

Table 2. Integrating Fuzzy Logic, Nearness, and IoT in Healthcare

Aspect	Description	Integration of IoT ,Fuzzy Logic, and Nearness,
Fuzzy Logic in Health Data Processing	Utilizing fuzzy logic algorithms to handle imprecise health data collected by IoT devices.	IoT devices gather health data, and fuzzy logic is applied to interpret data considering its inherent uncertainty.
Nearness Monitoring for Patient Safety	Implementing nearness and proximity spaces in healthcare settings using IoT to enhance patient safety	IoT devices equipped with proximity sensors monitor distances, ensuring patients and

	and social distancing compliance.	healthcare providers maintain safe distances.
Real-Time Data Collection and Analysis	Employing fuzzy logic for real-time data analysis in healthcare, enabling timely decision-making.	IoT devices collect real-time health data, and fuzzy logic is used for on-the-fly data analysis to provide accurate insights.
Enhanced Patient Engagement with Fuzzy Insights	Empowering patients with access to their health data and fuzzy-driven insights for proactive health management.	Wearable IoT devices provide patients with fuzzy-assisted health insights, promoting active engagement in healthcare decisions.
Fuzzy-Optimized Workflow Automation	Utilizing fuzzy logic to optimize healthcare workflows, allocate resources efficiently, and enhance overall efficiency.	IoT integration in healthcare leverages fuzzy logic for resource allocation and workflow optimization based on real-time data inputs.

5. Future Prospects and Consideration

Ongoing advancements in IoT technologies, such as miniaturization, improved connectivity, and edge computing, will further expand the possibilities of IoT in healthcare. These trends may lead to the development of more sophisticated wearable devices, smarter infrastructure, and innovative applications for patient care. The paper also sets the stage for exciting avenues of research and innovation in the realm of IoT in healthcare. Integrating fuzzy logic, nearness monitoring, and IoT, showcases the potential for addressing healthcare's evolving challenges. Integrating emerging areas such as artificial intelligence and machine learning algorithms with IoT data can unlock valuable insights and predictive capabilities [19]. Healthcare providers can improve diagnostics, predict disease progression, and personalize treatment plans by analyzing large volumes of patient data collected through IoT devices. AI-powered analytics can also help identify patterns and anomalies for early detection of health issues [20,21].

As IoT adoption in healthcare grows, a critical need emerges for integrating these technologies with existing health information systems like electronic health records (EHRs) which has huge potential in mental health rehabilitation [22]. Seamless sharing and accessibility of patient data across clinical, medical, genomic, and IoT sensor platforms can construct a 360-degree view of an individual's health. This could enable accurate diagnosis, personalized treatments, and continuous care coordinated across providers [23]. However, progress needs concerted efforts towards open, standardized application programming interfaces (APIs) and interoperability protocols that allow platforms to communicate [24, 25]. Health data portability should also be enabled through common standards to give patients transparency over and ownership of their data. Policy steps pushing interoperability, like those related to EHRs, will be instrumental in realizing the vision of integrated connected healthcare powered by the coming together of health tech ecosystems [26-29].

6. Conclusion

The introduction of IoT in healthcare signifies a remarkable leap forward, inaugurating an era characterized by interconnected, data-driven, and patient-centric healthcare. Incorporating cutting-edge techniques such as AI and fuzzy logic, as discussed, enhances IoT's capabilities, offering personalized and proactive decisions. Although the advancements in IoT for healthcare hold great promise, ethical concerns, challenges, algorithmic transparency, and accessibility issues are much required in this field. In the case study conducted on the data obtained from the open source repository, the VGG 16 model demonstrated more consistent improvement over the epoch, achieving higher validation accuracy than other models, whereas the discrepancies in validation accuracy and loss indicate the degree of variability of these models. For further research, this work can be enhanced for more epochs, and then results can be more explored.

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