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# Deep Learning-Based Classification for Healthcare-Based IoT System for Efficient Diagnosis

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**Abstract:** The Internet of Things (IoT) is a rapidly evolving technology in the realm of computing that aims to standardise the networking of previously disparate objects. IoT is relevant to many industries because to its accessibility, flexibility, portability, and energy efficiency. This includes wearable gadgets, smart cities, smart homes, smart cars, agriculture, supply chain, and retail. IoT also plays a crucial role in the healthcare sector by reducing the burden on more conventional healthcare infrastructure. IoT based healthcare solutions have been used to track patient information in real time. Data acquired via IoT-enabled health care apps may now be processed without the need for feature engineering, thanks to recent developments in deep learning (DL). In this chapter, we give a comprehensive overview of IoT-based healthcare systems with regard to DL models, based on a variety of case studies. In this research paper, DL in IoT-based healthcare systems, including its current popularity, potential applications, obstacles, and research priorities has been considered.

***Keywords:*** *Deep learning-based, Healthcare, IoT , Accuracy, Performance, Potential application, obstacles, research priorities.*

## 1. Introduction

### 1.1 Deep learning

In ML, DL is a discipline built on the back of ANN theory. To assess and learn from incoming data, computers use computational models called ANNs, which are made up of interconnected nodes called neurons. Each layer in a DNN that is completely linked has connections to the layers below it and the input layer. In a neural network, all neurons may receive input from the layer of neurons above them or from the input layer itself. In a neural network, one neuron's output feeds into the input for the next neuron in the next layer, and so on, until the last layer produces the network's final output. In order for the neural network to learn complex representations of input data, each layer of the network facilitates the transformation of the data via a series of nonlinear operations. Because of its impressive results in several applications such as CV, NLP, and RL, DL has recently risen to prominence as a highly visible subfield in machine learning.

Multiple ML paradigms, including supervised, unsupervised, and reinforcement learning, may make use of DL.A diverse range of methods is used to process these.

1. First, in supervised ML, a NN is taught to make predictions or classify information by analysing labelled datasets. The input features and the outcome variables are both considered inputs here. By learning to minimise the cost or mistake caused by the gap between predicted and target values, a neural network is trained to create predictions. Back propagation is a common name for this repeated process. Many supervised tasks make use of deep learning methods like CNNs and RNNs, including but not limited to picture classification and recognition, sentiment analysis, and language translation.

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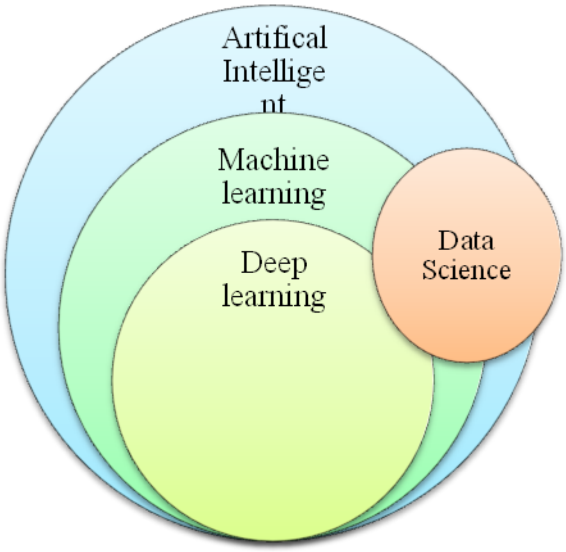


**Fig 1** Deep learning

2. Unsupervised machine learning refers to a process whereby a neural network is trained to identify patterns or cluster datasets without the use of labelled data. In this context, the absence of target variables is seen. The computer must be able to discover on its own any hidden patterns or connections in the datasets. Autoencoders and generative models are two types of deep learning that find widespread usage in unsupervised tasks including grouping, dimensionality reduction, & anomaly detection.
3. Reinforcement Machine Learning (RL) refers to a machine learning approach whereby an agent is trained to make optimal choices within a given environment in order to maximise a reward signal. The agent engages in environmental interaction via the process of executing actions and afterwards monitoring the rewards that ensue. Deep learning has the capability to acquire policies, which are defined as a collection of actions, with the objective of optimising the overall reward accumulated over a certain period. Deep reinforcement learning techniques such as Deep Q networks and Deep Deterministic Policy Gradient (DDPG) are often used in the reinforcement of many tasks, including robotics and game playing, among others.

**1.2 Deep learning-based classification for healthcare-based IoT system**

Deep learning-based classification is a powerful tool for improving the efficiency and accuracy of diagnosis in healthcare-based IoT systems. IoT devices can collect a vast amount of data from patients and medical equipment, and deep learning algorithms can help make sense of this data to aid in the diagnosis and treatment of various medical conditions. Here's how you can implement deep learning-based classification for efficient diagnosis in a healthcare-based IoT system:

- Data Collection: Deploy IoT sensors and devices to collect relevant healthcare data. These devices can include wearable sensors, medical imaging equipment, electronic health records (EHR) systems, and more. Ensure data privacy and security measures are in place to protect sensitive patient information.
- Data Preprocessing: The acquired data should be subjected to a cleaning and preprocessing procedure in order to eliminate any unwanted noise, address any missing values, and ensure that the data formats are standardised. The inclusion of this stage is crucial in ensuring the efficacy of deep learning models.
- Data Annotation: Annotate the collected data with appropriate labels. For healthcare diagnosis, these labels may include disease categories, severity levels, or other relevant information.
- Model Selection: Selecting a suitable deep learning architecture for the categorization problem is crucial. Typical options include convolutional neural networks (CNNs) for image data, recurrent neural networks (RNNs) for time series data, and more intricate structures such as transformers for organised and unstructured data.
- Training: Split your data into training, validation, and testing sets. Train the deep learning model using the training data. You may need a large amount of labeled data for this step, and data augmentation techniques can be used to increase the dataset size if necessary. Fine-tune hyperparameters to optimize model performance.
- Model Evaluation: Evaluate the efficacy of the deep learning model by using the validation dataset. Prominent assessment measures often used in classification tasks include accuracy, precision, recall, F1-score, and ROC (AUC) are all measures of how well a test can predict the true outcome.
- Deployment: Deploy the trained model to the healthcare IoT system. Ensure that it can efficiently process data in real-time or near-real-time, depending on the application.
- Continuous Monitoring: Implement a system for continuous monitoring of model performance in the production environment. Retrain or update the model as needed to adapt to changing data distributions and to improve accuracy.
- Interpretability: Deep learning models can be complex and difficult to interpret. Implement techniques for model explainability to make the

diagnosis process more transparent and trustworthy for healthcare professionals.

- Regulatory Compliance: Ensure that your healthcare IoT system and deep learning models comply with relevant healthcare regulations and standards, such as HIPAA in the United States or GDPR in Europe.
- Collaboration with Healthcare Professionals: Collaborate closely with healthcare professionals to integrate the deep learning-based classification system into their workflow and decision-making process. Their input is invaluable for achieving accurate diagnoses.

**1.3 IoT and Deep Learning in Healthcare**

IoT and deep learning technologies have potential to revolutionize healthcare by enabling more efficient, personalized, and data-driven healthcare services. Here's an overview of how IoT and deep learning can be combined in healthcare:

- Remote Patient Monitoring: IoT devices like wearable sensors, smart watches, and medical implants can continuously collect Patient data. Deep learning algorithms can analyze this data in real-time to detect anomalies or trends, providing early warnings for health issues like arrhythmias, falls, or respiratory problems.
- Predictive Analytics: Deep learning models can process historical patient data along with real-time IoT data to predict disease progression, hospital readmissions, or adverse events. This can help healthcare providers intervene proactively and allocate resources more effectively.
- Disease Detection: Deep learning algorithms can be trained on medical imaging data from IoT-connected devices such as X-ray machines, CT scanners, or MRI machines to detect and diagnose diseases like cancer, diabetic retinopathy, or neurological disorders with high accuracy.
- Drug Discovery: Deep learning models can analyze vast amounts of molecular data from IoT devices and databases to identify potential drug candidates, predict their efficacy, and accelerate drug discovery processes.
- Personalized Treatment: IoT data, combined with deep learning, can create personalized treatment plans for patients based on their unique health profiles. This can include personalized medication dosages, dietary recommendations, and exercise regimens.
- Healthcare Workflow Optimization: IoT devices can monitor the usage and availability of medical equipment, hospital beds, and other resources. Deep learning algorithms can optimize resource allocation, predict equipment failures, and streamline healthcare workflows.
- Natural Language Processing: DL models in NLP, can analyze electronic health records, clinical notes, and patient communication data to extract valuable insights for diagnosis, treatment planning, and research.
- Security and Privacy: As healthcare IoT devices collect sensitive patient data, deep learning can be used for robust security and privacy protection, including anomaly detection for data breaches and encryption techniques.
- Rehabilitation and Assistive Devices: IoT-connected rehabilitation and assistive devices, such as exoskeletons and prosthetics, can benefit from deep learning for better customization and real-time adaptation to a patient's needs.
- Telemedicine and Telehealth: IoT devices can enhance telemedicine by providing doctors with real-time patient data during remote consultations. Deep learning can assist in interpreting this data and making informed decisions.

## 2. Related Works

There are different researches in area of DL & healthcare that performed significant role in IoT based implications.

M Amin et al (2020) introduced DL-based features detector was used to identify malware; it was easy to train and could be used with other classifiers to assess an app's actions. The detected malware may be easier to identify in future efforts if the detector has learnt any distinguishing features. With a 98.97% F1-Score and a 98% success rate, their results show that the suggested feature detector produces remarkable results [1].

P. R. Jeyaraj et al. (2020) focused on the use of a DL algorithm in an Internet of Things-based smart healthcare setting for the categorization of atrial fibrillation. Several cases of atrial fibrillation were studied using same time series data collected by the Internet of Things-based e-health system, they had conducted a quantitative comparison study of various classification algorithms. They compared the performance of our proposed algorithm's learnt features on a signal categorized cases of atrial fibrillation to that of more traditional classifier. They measured a 96.3 percent success rate, having a 93.5 percent sensitivity and a 97.5 percent accuracy. The results show that an IoT based smart healthcare system may benefit from processing with the proposed deep CNN by received dependable, timely assistance and correct categorization of ECG signals [2].

S. Sharma et al. (2020) reviewed health care framework powered by deep learning for assisted those with Alzheimer's disease using the IoT. They present DeTrAs, an Internet of Health framework based on deep learning that may aid people with Alzheimer's disease. Three stages make up DeTrAs's operation: It was suggested to employ sensory movement data in a A method is designed for anomaly monitoring in people with Alzheimer's disease, and a RNN is used for Alzheimer's disease prediction. (a) a CNN-based emotion detection method (and) (b) a timestamp window-based NLP scheme. When compared to other current machine learning algorithms, DeTrAs was shown to be around 10-20% more accurate in its evaluations [3].

I. Ahmed et al. (2020) presented covid-19 pre-screen using an IoT-based deep learning system. The goal of this research was to create an early assessment system for Covid-19 utilising an IoT-based DL architecture. This strategy has the potential to reduce stress for busy doctors and radiologists in addition to helping with pandemic containment efforts. utilising a DL-based model, namely faster region utilising CNNs (Faster-RCNN) and ResNet-101, we were able to successfully identify Covid-19 in chest X-rays. In order to do detection, it employs a region proposal network (RPN). When using the model, they were able to improve detection accuracy to 98%. They conclude that the method has the potential to aid the medical expert/radiologist in verifyed the early evaluation towards Covid-19 [4].

A. H.Sodhro et al. (2018) explained IoT & healthcare product lifecycle management were converged. The first issue was addressed in this study by combining IoMT and PLM to control the flow of data from one entity to another and from one device to another. While addressing the second problem, they proposed two algorithms one based on battery recovery (BRA) to manage the battery lifespan and the other based on joint energy harvested and duty-cycle optimization (JEHDO) to manage the energy of the resource-constrained small wearable devices. In addition, a unique framework built on IoMT and PLM is offered for use in medical treatment. According to find of experiments, both BRA & JEHDO save both energy & battery life [5].

Md. M. Islam et al. (2020) created Smarter healthcare monitoring based on IoT. Based on their findings, they suggested an IoT-powered smart healthcare system that would be able to track a patient's vitals and their immediate surroundings in real time. The hospital set had five sensors: a heart rate sensor, a body temperature sensor, a room temperature sensor, a carbon monoxide sensor , & a carbon dioxide sensor.The created technique has an error rate that was consistently below a set threshold ( 5%) [6].

H. A. E. Zouka et al. (2021) created an intelligent healthcare monitoring system based on the Internet of Things. Connecting medical devices securely via the Internet to provide cutting-edge health monitoring.The purpose of this paper is to demonstrate how artificial intelligence technology, specifically neural networks and fuzzy systems, can be incorporated into a secure healthcare monitoring system to make it operate as a smart healthcare model that decides the priority on its own based on the collected health parameters from the senor nodes. The proposed model employs a trust environment to gather verified patient vitals, transmit them via GSM module to Azure IoT Hub, and process them with a logic-based algorithm trained in a FBIS to produce a linguistic representation that can be used to assess the patient's condition. Therefore, the proposed method enables safe, precise, real-time monitoring of patients. In the following sections, they would examine how the FBIS may communicate with a private healthcare monitoring network to get up-to-date patient status information and convey that information to a medical advisor for prompt action. [7].

X. yang et al. (2020) introduced knowledge graph study of developed internet of things technologies for smart health research. One of most important uses for IoT devices has been "smart health." With CiteSpace and other bibliometric techniques, they analyse 9561 publications published in the area of IoT-based smart health research between 2003 and 2019 using data from Web of Science core collection. [8].

S. Akhbarifar et al. (2020) looked encrypted system for remote health monitoring with the goal of early illness detection in the Internet of Things cloud. Patients' private information was protected using a lightweight secure block encryption technology, & crucial events were predicted using data mining techniques applied to their biological data as detected by smart medical IoT equipment. Lightweight block encryption techniques have a significant practical influence on IoT platforms due to the latter's resource constraints. The experimental findings show that when compared to the RF, MLP, SVM, and J48 classifiers, the K-star classification method provides the best overall performance, with 95% accuracy, 95% precision, 95% recall, and 93.9% f-score. In light of these findings, it was clear that the proposed method is effective in developing a remote health monitoring model supported by protected IoT data in cloud-based IoT environments. [9].

W. Sun et al. (2018) reviewed the privacy and data protection for the IoT in healthcare. The MIoT has come a long way since its inception, playing a crucial role in improving health, safety, and welfare of billions of people. In comparison to people physically visiting a hospital, efficiency, convenience, & cost performance of healthcare were considerably improved by the use of remote, continuous, and real-time monitoring of health-related factors, followed by processing and transmission to a medical data centre. As the amount of data processed by MIoT devices grows, there is a corresponding rise in the likelihood that sensitive information may be leaked. The security and privacy of data obtained by MIoT devices, whether in transit to or stored in the cloud, raises significant challenges that have yet to be resolved. [10].

V. Ravi et al. (2022) Introduced Attention-based multi-dimensional DL was used by IoMT to identify & categorize malware in cyber-physical healthcare systems.For a malware detection and classification system that works across different IoMT architectures, this research provides an attention-based multidimensional DL approach that uses byte sequences collected from Executable and Linkable Format files. The DL approach leverages automation to speed up feature creation and extraction from unprocessed data. The proposed approach also simplifies identifying an ELF file's CPU architecture. They presented a comprehensive experimental research and evaluation on the IoMT cross-architecture benchmark dataset. The proposed approach beat the results obtained from numerous existing techniques across all trials, achieving 95% accuracy in IoMT malware detection, 94% accuracy in IoMT malware classification, and 95% accuracy in CPU architectures classification.[11].

V. Ravi et al. (2022) reviewed the deep learning framework that uses multi-view attention to identify malware in intelligent healthcare systems. The proposed method outperforms ML-based and non-attention-based algorithms for malware detection with 95% accuracy, using features from the PE-Header, & API calls. Detecting viruses using images on Windows and Android operating systems, with extensive evaluation results. On the Windows-based dataset, the proposed technique obtained 98% accuracy, whereas on the Android-based dataset, it reached 97% accuracy. When compared to established methods, the novel approach proved superior in spotting malicious software. Experimental findings on three malware datasets demonstrated that the proposed technique was resilient & generalizable for malware detection in smart healthcare systems. [12].

## 3. Problem Statement

Deep learning-based classification for healthcare-based IoT systems can offer several benefits, but it also comes with its own set of challenges & problems. Here are some common issues you may encounter when implementing deep learning for efficient diagnosis in healthcare IoT systems:

1. Data Quality and Quantity: To train properly, DL models need massive volumes of high-quality data. Privacy considerations and the necessity for subject knowledge make it difficult to get labelled data in the healthcare industry. As a corollary, data inconsistency might cause inaccurate predictions to be made.
2. Data Privacy and Security: Healthcare data is sensitive and must be handled with extreme care to comply with privacy regulations like HIPAA.
3. Interoperability: Different manufacturers' IoT devices in healthcare may use various communication standards. Ensuring that these devices can seamlessly integrate and share data for deep learning models can be complex.
4. Model Interpretability: DL models were often considered as "black boxes," making it challenging to explain their decisions. In healthcare, it's crucial to understand why a model made a particular diagnosis for transparency and trust.
5. Generalization: Models trained with deep learning may overfit their data, resulting in worse performance on novel data. This is especially problematic in healthcare where patient populations and conditions may vary significantly.
6. Ethical Concerns: There are ethical concerns regarding the use of AI in healthcare, such as potential biases in the training data leading to disparities in care, and the need to maintain a human-in-the-loop approach for critical decisions.
7. Regulatory Approval: Healthcare AI systems must often go through rigorous regulatory approval processes, which can be time-consuming and expensive.

## 4. Proposed Work

To address these challenges, a multidisciplinary approach involving data scientists, healthcare professionals, and experts in ethics and regulations is essential. Additionally, ongoing research and development in AI for healthcare are critical to advancing the field and overcoming these issues while prioritizing patient safety and privacy.

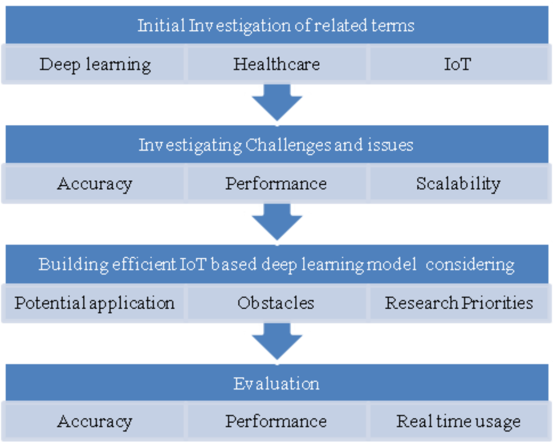


**Fig 2** Process flow of proposed work

## CNN

Increased accuracy in face recognition is possible because of the intelligent CNN's ability to correctly extract characteristics of faces from improved face image datasets [15-19]. In this research, a CNN model is used to recognize people's faces for the purpose of the attendance log. Because of this, the model may learn to recognize the number of faces in a given picture as well as their relative placement within that image. CNN's use of image processing has the potential to provide important gains. Artificial neural networks, specifically CNNs, were designed to interpret pixel input during image detection and processing. It is possible to learn many filters for each layer. Each filter has been programmed to identify a unique set of patterns or characteristics. These traits and tendencies are exclusive to that filter. This section has expanded on many CNN models used for picture identification and classification [20-26]. However, research is investigating the merging of the Inception and DenseNet models.

## LeNet

The LeNet model of CNN, established in 1998, is not only the most well-known but also the initial type of CNN. Since it is constructed using convolutions, pooling, and fully connected layers, LeNet is a prototypical CNN. Handwritten digit recognition was a mandatory job on the MNIST dataset. The design was a major inspiration for subsequent networks like AlexNet and VGG. [27-30].

## VGGNet

The VGG is a multi-layered, deep CNN architecture similar to the industry standard. The VGG-16 network is 16 convolutional layers deep and was trained on over a million images from the ImageNet database. [34]. These models have poor accuracy, and pre-trained VGG often perform better. Innovative object recognition models often employ the VGG framework as their foundation. The VGGNet is now used as a benchmark in many other applications and datasets outside ImageNet. Even now, it is among the most widely used designs for image recognition.

## AlexNet

AlexNet is a state-of-art architecture for object identification that might have significant implications for the field of computer vision AI research. These are pre-trained models and have limited scope. The first significant CNN model to incorporate GPU training was AlexNet. This made model training go more quickly. In comparison to LeNet, AlexNet has a deeper architecture (8 layers), making it more able to extract features. With color visuals, it also performed well for the time.

## ResNet

The Residual Network, sometimes known as ResNet, is a DL model represented in Fig 1, that may be used for computer vision tasks. However, it is providing high accuracy but it has certain limitations such as a lack of flexibility that could be overcome by integrating it into other models. It is an architecture known as a CNN, and it was built to be able to accommodate hundreds or thousands of convolutional layers. The use of ResNet has resulted in a considerable improvement in the performance of neural networks consisting of additional layers. When comparing ResNet-34 with plain-34, When comparing the two in terms of the mistake rate they both create, a clear distinction emerges [33].

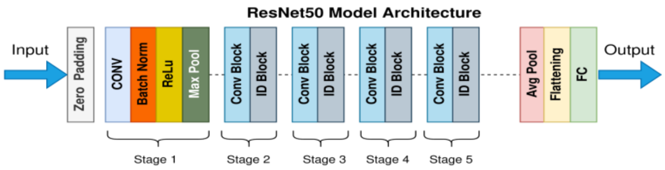


**Fig 1.** ResNet50 model Architecture [33]

## DenseNet

It is a CNN because each layer talks to the one below it. For example, the first layer of a DenseNet network talks to the second layer, and so on [34]. If used alone, dense networks are inefficient. The DenseNet architecture was created to make DL networks more efficient and effective while also reducing their training costs. As seen in Fig. 2, this is achieved by decreasing the distances between the architecture's various levels.

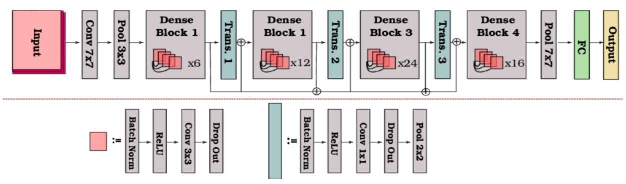


**Fig 2.** DenseNet Architecture [34]

## Inception

Inception V3 is a CNN that can analyse & recognise images. Its first conception was as a plug-in for GoogleNet. Training a model using an Inception network is time-consuming and yields only moderate accuracy. One part of CNN's picture model is the Inception Module, which estimates the optimal local sparse structure [34]. In layman's terms, It allows us to apply several filter sizes inside a single picture block, which can then be combined and passed on to the subsequent layer. Previously, as seen in Fig. 3, we could only use a single filter size.

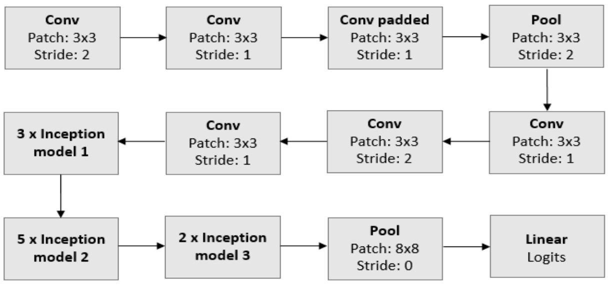


**Fig 3.** Inception V3 Architecture [34]

## 5. Result and Discussion

In this section different IoT Based healthcare have been discussed that focused on deep leaning in order to perform classification in order to detect severe diseases. Dataset for training has been obtained from kaggle. This image set is considering image required during Brain tumor detection, kidney stone detection, Blood cancer detection, Covid Detection. After training of CNN model, images are passed for testing to get accuracy. 5000 image of kidney stone has been used during testing and table 1 is presenting confusion matrix. Considering table 1, table 2 has been obtained to present accuracy.

**Table 1** Confusion matrix in case of kidney stone detection

| | Detected | Not Detected |
|---|---|---|
| Detected | 4984 | 6 |
| Not Detected | 16 | 4994 |

TP: 9978 and Overall Accuracy: 99.78%

**Table 2** Accuracy table for kidney stone detection

| Class | n (truth) | n (classified) | Accuracy |
|---|---|---|---|
| 1 | 5000 | 4990 | 99.78% |
| 2 | 5000 | 5010 | 99.78% |

5000 image of Brain has been used during testing and table 3 is presenting confusion matrix. Considering table 3, table 4 has been obtained to present accuracy during detection of brain tumor.

**Table 3** Confusion matrix in case of Brain tumor detection

| | Detected | Not Detected |
|---|---|---|
| Detected | 4987 | 4 |
| Not Detected | 13 | 4996 |

TP: 9983 and Overall Accuracy: 99.83%

**Table 4** Accuracy table for Brain tumor detection

| Class | n (truth) | n (classified) | Accuracy |
|---|---|---|---|
| 1 | 5000 | 4991 | 99.83% |
| 2 | 5000 | 5009 | 99.83% |

3500 records are considered for Blood cancer detection during testing and table 5 is presenting confusion matrix. Considering table 5, table 6 has been obtained to present accuracy during detection of blood cancer.

**Table 5** Confusion matrix in case of Blood cancer detection

| | Detected | Not Detected |
|---|---|---|
| Detected | 3497 | 4 |
| Not Detected | 3 | 3496 |

TP: 6993 and Overall Accuracy: 99.9%

**Table 6** Accuracy table for Blood cancer detection

| Class | n (truth) | n (classified) | Accuracy |
|---|---|---|---|
| 1 | 3500 | 3501 | 99.9% |
| 2 | 3500 | 3499 | 99.9% |

4000 records are considered for COVID 19 detection during testing and table 7 is presenting confusion matrix. Considering table 7, table 8 has been obtained to present accuracy during detection of COVID 19.

**Table 7** Confusion matrix in case of COVID 19detection

| | Detected | Not Detected |
|---|---|---|
| Detected | 3996 | 5 |
| Not Detected | 4 | 3995 |

TP: 7991 and Overall Accuracy: 99.89%

**Table 9** Accuracy table for COVID 19 detection

| Class | n (truth) | n (classified) | Accuracy |
|---|---|---|---|
| 1 | 4000 | 4001 | 99.89% |
| 2 | 4000 | 3999 | 99.89% |

Comparative analysis of accuracy in case of different applications has been shown in following figure

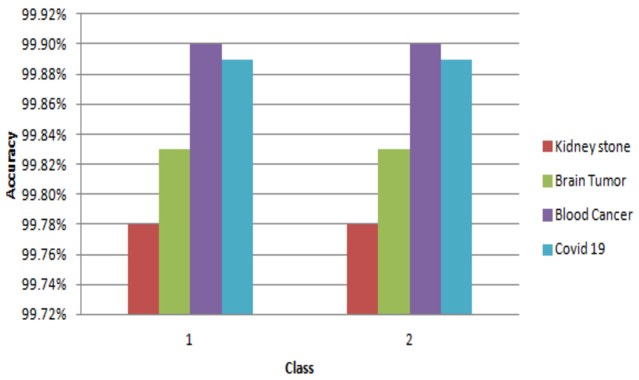


**Fig 3** Comparison of accuracy in case of different applications

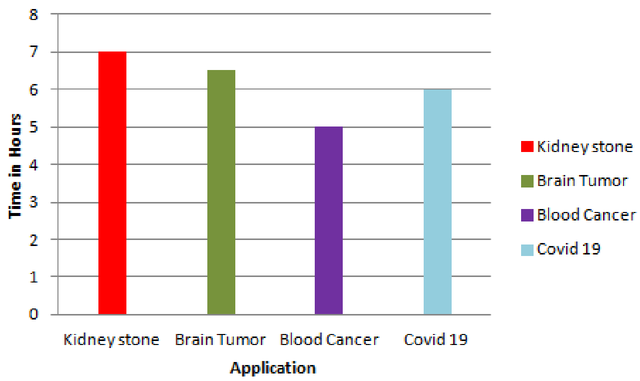


**Fig 4** Performance comparison in case of training and testing of different models

## 6. Conclusion and Scope of Research

It has been noticed that in an IoT based healthcare setting, DL based categorization has played an important role in the diagnosis of brain tumours and kidney stones, Blood cancer detection, Covid 19 Detection. It is observed that proposed work has provided accuracy above 99% during classification where as average recall, precision and F1-Score is above 0.99. Moreover it is observed that dataset with large number images takes more time as compared to dataset with smaller number of images. It has been observed that dataset, epochs, batch size , learning model plays significant role in accuracy enhancement during image classification using deep learning approach.

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