Journal of Data Analysis and Information Processing, 2026, 14(3), 356-375
https://www.scirp.org/journal/jdaip
ISSN Online: 2327-7203
ISSN Print: 2327-7211

Arab Region Intelligent Medical: Using Secure IoT Protocols and Deep Convolutional Neural Networks for Healthcare Optimization

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How to cite this paper: Sayed, M. and Mohamed, H. (2026) Arab Region Intelligent Medical: Using Secure IoT Protocols and Deep Convolutional Neural Networks for Healthcare Optimization. *Journal of Data Analysis and Information Processing*, **14**, 356-375.
https://doi.org/10.4236/jdaip.2026.143018

Received: June 24, 2026
Accepted: August 15, 2026
Published: August 18, 2026

Abstract

Recent advances in intelligent healthcare have led to the development of deep convolutional neural networks and standardized rules for connected devices, two key building blocks for automated healthcare diagnosis and remote patient monitoring systems. This paper proposes an integrated healthcare framework supported by the Internet of Things, leveraging smart medical devices, secure communication protocols, and deep learning. The framework processes medical images and physiological data using IoT-enabled devices, supported by robust, lightweight transmission protocols. This study focuses on medical care systems in the Arabic-speaking world, where an inadequate supply of healthcare professionals and the remote locations of healthcare facilities pose challenges to efficient diagnosis and continuous care monitoring. To address communication problems in IoT healthcare networks, the study proposes an intelligent routing algorithm that detects network failures and prioritizes critical medical information during transmission. The proposed framework addresses IoT problems such as cyberattacks, congestion, delays, jitter, and limited bandwidth while preserving secure data communication. Additionally, the text addresses cultural and societal concerns specific to Arab countries. It emphasizes the importance of balancing transparency in medical practices with the advancement of IoT technologies to safeguard patient privacy. Experimental results on the transmission of medical images and healthcare information using IoT communication protocols indicate high training and validation accuracies and a low mean squared error for the deep learning algorithm.

Keywords

Artificial Intelligence of Things, Deep Convolutional Neural Networks, E-Health Care Systems, Internet of Things, Reading Complex Data

1. Introduction

The adoption of sensor technology has become essential in the Arab world because of weak digital health infrastructure and a shortage of qualified experts. The Internet of Things (IoT) forms a connected network of digital devices that use remote sensors to collect and transmit data. It has been used in modern healthcare systems to develop treatment methods, including remote patient monitoring, real-time biomedical data analysis, and personalized medicine. Convolutional neural network (CNN) technology has proven highly efficient at processing large volumes of data, especially visual data [1] [2]. Deep convolutional neural networks (DCNNs) have proven highly effective in addressing a broad spectrum of issues, including image recognition, image segmentation, fraud detection, spam filtering, natural language processing, and more. They are particularly relevant in the medical imaging field due to their effectiveness in detecting patterns and abnormalities in diagnostic images [3]-[5].

Therefore, by incorporating connected sensing devices that collect health data and deep learning frameworks for processing, Arab countries will be able to develop public health services and create modern systems that will enhance the accuracy of diagnoses and treatments [6]. In this context, deep learning can be considered the ideal solution in healthcare due to its immense potential to analyze, diagnose, and treat medical images. As is well known, convolutional deep learning models are multi-layered networks that learn via backpropagation and can extract salient features by applying filters, thereby mitigating overfitting and noise. Although a fully connected layer incurs a high computational cost and can be avoided, convolutional layers are ideal for handling two-dimensional spatial data because they require few parameters to encode spatial information [7]. Here, the performance of the networks is determined by the weight matrices between the layers [8]. Over time, numerous CNN architectures have been proposed as feature extractors [9]-[13]. Some popular architectures that emerged from the competition include LeNet [9], AlexNet [8], VGG [11], GoogleNet [10], ResNet [14], and DensNet [13]. In this experiment, we implemented the VGG network to establish accuracy.

1.1. E-Health in Arab Countries

Arab countries are rapidly advancing digital transformation in the healthcare sector, striving to improve the quality of care, increase service efficiency, and broaden access to healthcare. To improve the quality of medical services and manage patient data efficiently, many are integrating digital health systems into their infrastructure, with support from the World Health Organization [15]. Modern healthcare systems are making it easier for people in remote and rural areas to connect with healthcare providers through the growing use of telemedicine. This means residents can now access high-quality healthcare right where they are, bringing medical support closer to home. Saudi Arabia is a leading Arab country in digital health, having launched several initiatives, such as the National Health Information System and the Telemedicine Network, to provide citizens with electronic health records and remote medical services. The United Arab Emirates has also developed smart government healthcare services across all its emirates, making it easier for citizens and residents to access their clinical information, use telemedicine, and book appointments online. Egypt has launched a major e-health initiative, known as the National Health Information System, to provide citizens with electronic health records and improve coordination among healthcare providers through electronic access. Similarly, Morocco has implemented a key e-health initiative, the national electronic health record system, to provide citizens with continuous care across medical facilities. Through the Qatari electronic health record system, citizens can access electronic health records, telemedicine, mobile health services, and remote communication between patients and clinical providers. To bridge the gap in underserved health areas, Lebanon recently launched its National Digital Transformation Strategy in Health, which uses digital tools as a "right, not a privilege." [16] In Kuwait, during development and implementation, the National Center for Health Information is working to activate a fully interconnected digital health system. For more information, interested readers are referred to [17] [18].

1.2. Deep Convolutional Neural Networks and Complex Data

A primary reason researchers favor deep convolutional neural networks is their exceptional capacity to handle complex data. While they are primarily used in image recognition, their real strength lies in learning intricate hierarchical feature representations. This allows these models to analyze complex data, including high-dimensional, high-noise, and otherwise difficult-to-analyze spatial and temporal signals. For example, when dealing with high-noise sensors, DCNNs can analyze time-series data by representing it as a spectral diagram or an image showing signal strength over time. Therefore, they can be used to analyze multidimensional health data, such as MRI, CT, and X-ray scans. These analyses enable the accurate detection of tumors, microfractures, and other defects that may not be visible through traditional methods [19]. Although relying on healthcare systems that use big data and artificial intelligence to improve epidemic prediction and design treatments tailored to each patient's needs has become a reality, it faces significant challenges, such as the digital divide and digital illiteracy in the Arab world.

1.3. Deep Convolutional Neural Networks in Healthcare

By leveraging deep convolutional neural networks for image recognition, doctors can accurately diagnose and classify diseases and help develop effective treatment plans. For example, a deep convolutional neural network was able to distinguish among distinct types of skin cancer using images of skin diseases [20]. Moreover, deep neural networks have been applied to diagnose diseases from CT scans, including cancer, stroke, and brain injury [21]. Segmentation is a promising area where deep learning models effectively identify specific body parts or detect abnormalities in medical images, offering crucial insights into disease progression and treatment effectiveness. A variety of DCNNs for tumor segmentation on MRI images to assist with surgeries have been introduced [22]. Deep convolutional neural networks can also be employed in popular medical natural language processing applications to analyze electronic health records, patient notes, and clinical documentation, thereby contributing to more informed decisions in personalized healthcare. One of the main challenges to implementing convolutional models in healthcare is privacy and security. Such networks require enormous amounts of training data, and it is necessary to guarantee their confidentiality and safety. The second challenge associated with the use of DCNNs is interpretability, as it is difficult to understand the logic behind their decision-making. Finally, there are ethical considerations related to machine learning applications that need to be addressed, such as discrimination and biased training, as the collected data may contain built-in prejudiced attitudes [23]; data ownership, informed consent, and automated decision-making are also issues to consider [24].

1.4. Related Work

In brief, a literature review will be conducted to assess the current state of research on the possibilities and limitations of using network sensing and deep learning in healthcare services, and it will be found that the application of deep learning techniques in medical imaging and diagnosis is gaining momentum [25]. In one application, CNNs are currently being used to analyze X-rays to identify diseases such as pneumonia and tuberculosis. In addition, machine-to-machine systems may be useful for technology-enabled medical services, especially in rural regions where access to clinic facilities is difficult. Many researchers discuss the advantages of combining deep learning and connected healthcare systems for electronic medical purposes. For example, Li *et al.* [26] propose developing a sensor-enabled intelligent system that uses CNNs to analyze medical imagery and assist doctors in diagnosis. Despite the limited number of such studies conducted across Arab countries, several projects have explored the potential use of deep learning and IoT in the medical technology sector. For example, a pilot project in Saudi Arabia employed wearable devices to collect health data and used machine learning to provide personalized health advice. It is known that there are problems with communication and the provision of patient care services in rural areas, and therefore, an Egyptian research team has developed a method that uses Internet of Things technology to monitor and treat patients remotely, highlighting the benefits of these technologies.

Although AI platforms, such as ChatGPT, Google, Gemini, and YouTube [27] [28], are popular in healthcare for their ability to provide quick, useful, and understandable information to doctors and their patients alike, these resources cannot be relied on absolutely. They must be used with caution, as they lack reliability and accuracy. Specifically, the algorithms used to search for the required data cannot evaluate the data's validity or context. Although information gathered through artificial intelligence or search engines may be accurate and easy to understand because of the ability to modify questions, it is essential to review the results with other clinical care professionals to fully understand their meaning. It is worth noting that information from these sources is often riddled with errors and frequently associated with potentially negative outcomes.

1.5. Problem Definition

With the advent of the Internet of Things in the medical field, a massive amount of complex data flows rapidly from various sources within the system in real time. Despite deep convolutional neural networks' ability to process this data, their introduction into IoT-driven medicine poses challenges. The main challenges include the complexity of machine learning algorithms and the limited computational capabilities of network-embedded systems, both of which impede deployment. Data quality problems, like inconsistency and incompleteness, further diminish performance and efficiency. Moreover, interpreting these models is difficult, thereby affecting their trustworthiness for medical use. Privacy issues are also significant, necessitating strong safeguards against data interception or tampering.

In this study, we propose a smart routing protocol, "Route Attack with Detection Algorithm" [29], that enhances security and reliability in IoT networks and helps prevent cyber threats, including DDoS attacks. The algorithm identifies unusual or trivial packets and routes important real-time traffic through a safe path before any network failure occurs. Our NS2 simulations revealed that this method decreases packet loss, latency, congestion, and network overhead, ensuring steady data flow. This is particularly important for time-sensitive applications like telemedicine and real-time video. We then explore tailored deep learning models for healthcare supported by connected infrastructure, focusing on their design, training, and practical deployment. We highlight that these models are vital for disease diagnosis, treatment strategy development, and personalized care. Additionally, we show that these models can analyze complex medical images, identify key features, and predict potential pathological conditions that could affect patient treatment. Despite some difficulties and ethical concerns associated with the application of these systems, their advantages are clear and promising. **Figure 1** illustrates how machine learning and IoT complement each other in healthcare.

This paper is structured as follows: Section 2 describes the data set, explains its characteristics, and details the preprocessing steps. Section 3 introduces the methodology. Section 4 presents the novel approach to developing the Deep Convolutional Neural Network model. Section 5 presents the experimental evaluation and results. Section 6 wraps up the paper by summarizing the key findings and suggesting directions for future research.

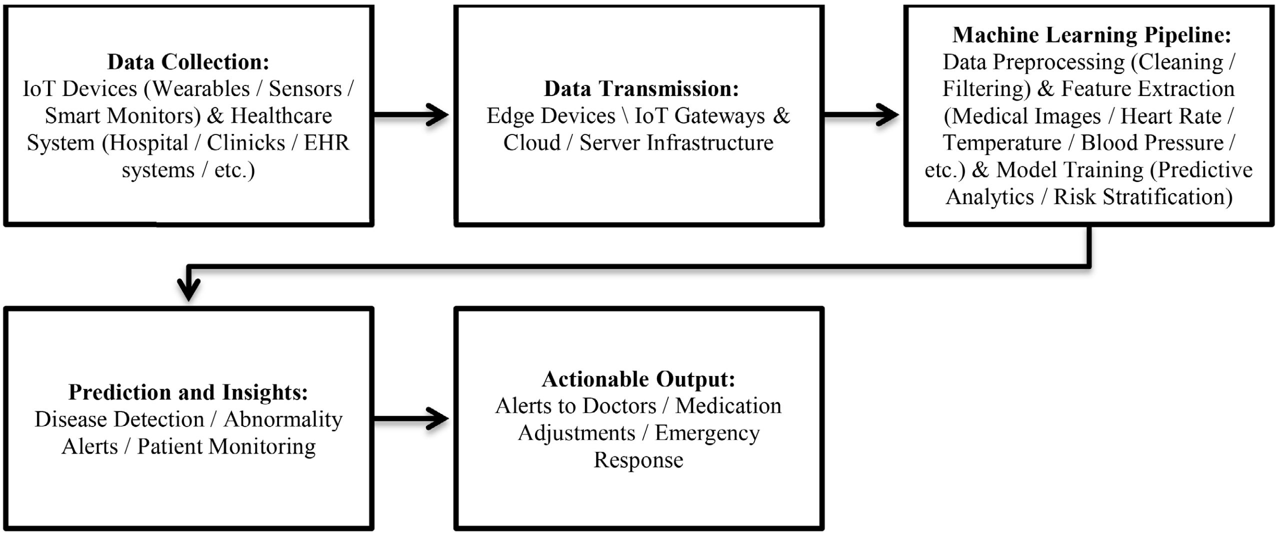

Figure 1. Machine learning and Internet of Things in healthcare.

2. Data Set

One of the most important aspects of integrating deep learning and Internet of Things technologies is ensuring that data collected by IoT devices remains secure during transfer to health management institutions for analysis and diagnosis. Smart health institutions must also protect patient confidentiality and privacy, as it is common in many Arab societies for health records to be managed within the family. Therefore, privacy is a fundamental aspect of treatment decision-making [30]. Here, we cannot overlook the social and cultural aspects, as they are integral to this process. Observing cultural sensitivities and privacy issues not only ensures safety but also builds trust with the patient regarding treatment. Cultural sensitivity is useful when overseeing healthcare data collected from patients through IoT ecosystems. Figure 2 provides an overview of the steps involved in protecting electronic health records. In addition, there are data challenges within the area. For instance, medical data are high-dimensional and include correlated and missing features.

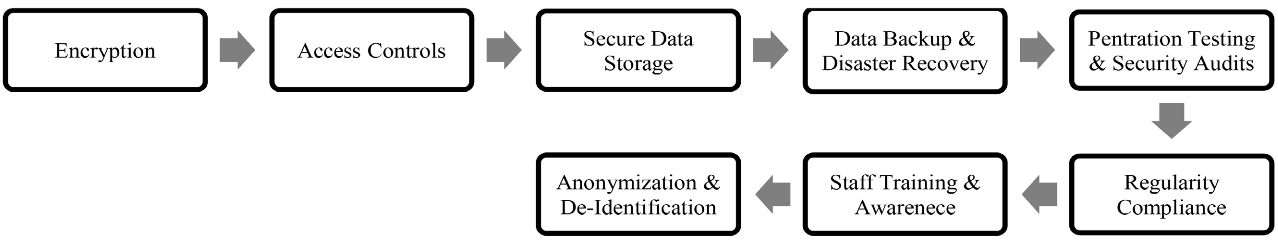

Figure 2. Data security and privacy protection guide.

In general, electronic health records contain diverse datasets, such as medical images, clinical documents, wearable sensors and monitoring devices, genomic and other genomic data, administrative information, and public medical data. In this work, we use medical image data to train and evaluate our model, as image data processing involves multiple stages. Histogram stretching of input facial images is performed to improve their quality, consistent with the findings provided in [31] and [32]. Furthermore, the image flipping technique [33] is employed to increase the sample size. In addition, other conventional pre-processing techniques, including data cleansing and normalization, encoding and feature extraction, missing value management, and data augmentation and balancing, are used; see [34] and [35]. Lastly, DCNN models employ a feature-based approach to analyze the images by matching features at similar locations across different images [10] [36]-[38].

Below are examples from among the many health-related databases readily available online, each offering a variety of health data types. We provide certain well-known free medical data sets on the internet and rate them on a 10-point scale to help readers and researchers make an appropriate choice depending on their preferences and needs **Figure 3** and **Figure 4**. Currently, there are no open-source Arabic health search databases that contain actual patient information or radiology images due to the confidential nature of health information and the privacy risks associated with such data. For instance, it is legally prohibited to publish patient data, such as medical records or images like X-rays and MRI scans, in the Arab world.

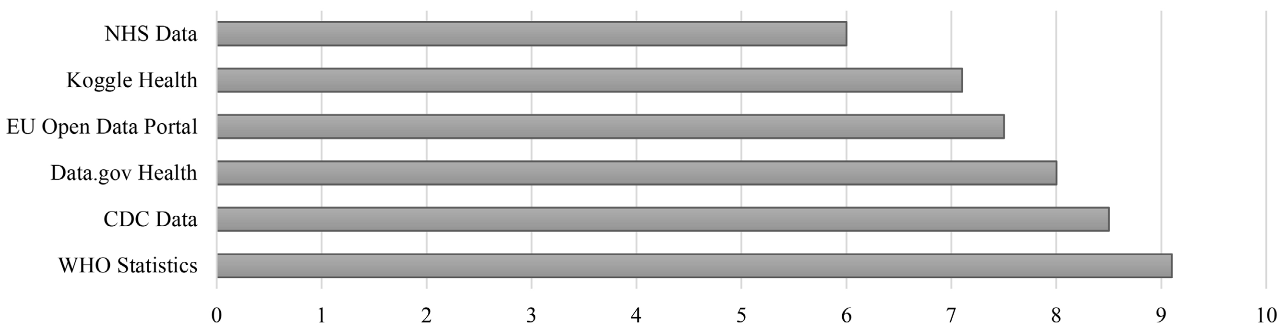

Figure 3. Popular free online health data sources.

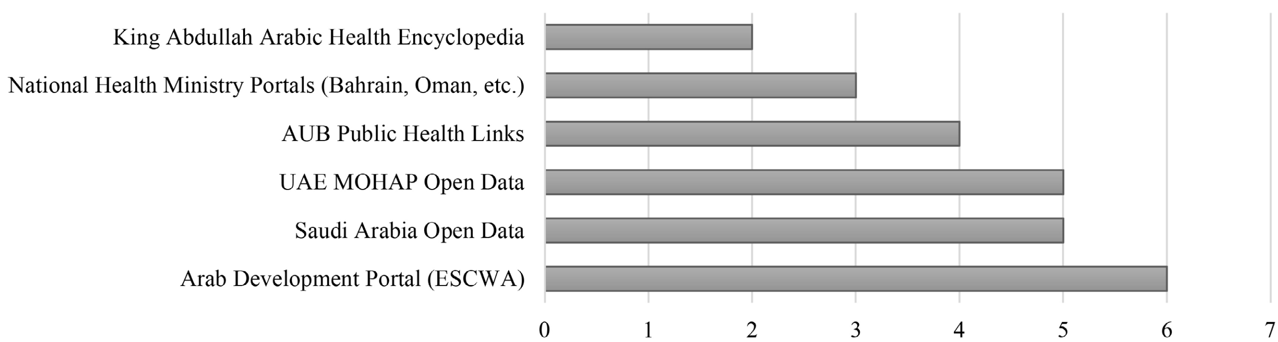

Figure 4. Arab free online health data sources.

3. Conceptual Framework and Methodology

As part of designing a technological procedure that keeps pace with rapid healthcare advancements in Arab countries, we are integrating DCNNs with interconnected smart objects and exploring their potential through a hybrid research methodology. The first step was an in-depth review of relevant literature, including scholarly articles, publications, and reports that specifically addressed this issue in the Arab context. For the literature review, we used PubMed, Web of Science, and Google Scholar and included only peer-reviewed English-language publications. We selected essential case studies that highlight various facets of deep learning and wireless sensors to gain a thorough understanding of the subject. Afterward, we consulted with healthcare professionals and officials responsible for deploying IoT solutions in clinical environments to discuss practical issues and ethical concerns. We followed the same strategy of using DCNNs to process visual data in real time, employing a mechanism similar to that used to detect objects in images captured by cameras installed, for example, in smart homes. Using deep learning, complex sensor data from smart environments is analyzed, enabling useful inferences to predict events or improve processes.

With faster systems such as 5G and fiber optics, IoT becomes essential for delivering real-time services, including health care applications. Nonetheless, data transmitted over IoT networks must be delivered reliably and on time. To evaluate the communication layer of the designed healthcare IoT systems, an efficient data routing mechanism [39] was considered, based on the cluster structure of smart medical networks. In general, the routing algorithm is designed to operate under a multi-criteria model that considers factors such as latency, buffer fill level, link stability, and remaining energy. This cluster-based approach enhances scalability, promotes high connectivity, prevents hotspot issues, and balances energy consumption. It enables the assessment of realistic network parameters and communication constraints while accounting for the high costs and privacy restrictions typical of patient care systems. Performance is evaluated using metrics such as packet delivery rate, average end-to-end delay, data transmission speed, routing overhead, and energy use. Transmitting data over IoT networks poses challenges, including cybersecurity threats, congestion, latency, packet loss, and jitter. The main concerns are twofold: ensuring immediate data reception despite cyber risks and enabling smart routing during disruptions. For example, in remote monitoring, emergencies, or surgeries, data reliability is critical because failures can lead to severe consequences. To address this challenge, a sophisticated data routing scheme based on the characteristics of current protocols is proposed. The key to this mechanism, described in [29], lies in using the route attack in conjunction with a detection protocol. This protocol detects network issues and reroutes priority medical data over uninfected paths, identifying both critical and non-critical packages. Additionally, this solution depends on monitoring schemes that identify urgent data in node buffers and trigger immediate delivery. A problem occurs if both the primary and secondary routes are compromised, delaying the rerouting. To prevent this, options include redirecting via neighboring nodes or sending packets directly from the source. Overall, this approach uses IoT technologies to optimize data transfer, automate traffic control, increase reliability, and ensure the timely delivery of critical healthcare data. Monitor the model's performance and s*et al*arms for abnormal behavior or faults. An extended function of cyber-physical systems is to transform healthcare from reactive to proactive through monitoring and data collection. For example, a system of connected devices, including wearable biosensors such as ECG and glucose sensors, implantable medical devices such as smart pacemakers, and various environmental sensors that measure home conditions, can be used to enhance safety when caring for elderly patients. The goal of using smart devices extends beyond data collection and communication. They also use edge computing to deliver instant notifications and support closed-loop systems, such as smart insulin delivery that activates based on analytical decisions. After passing through the communication channel, the data is sent to a cloud network for storage and is then analyzed with a deep learning algorithm.

To analyze data more effectively, make better decisions, and improve overall performance, it is essential to implement at least one strategy to enhance the training process. For instance, using fast activation functions such as ReLU increases efficiency and stabilizes training. Batch normalization normalizes neuron inputs, stabilizes gradients, and speeds up convergence. Advanced optimizers like Adam and RMSProp outperform basic gradient descent by adapting to the training process. Employing pre-trained models and fine-tuning them on specific datasets can save time and boost learning outcomes. Hardware accelerators such as GPUs and TPUs enable parallel processing, accelerating training. Regularization techniques such as dropout and weight decay prevent overfitting. Adding skip connections can enhance network performance. Active learning reduces the number of labeled samples needed for training. Additionally, data augmentation (e.g., rotating or scaling images) and mini-batches enable faster training without sacrificing accuracy. Next, we describe a five-layer convolutional model with max pooling and two dense layers, built in Python using Keras on TensorFlow. A dropout layer helps prevent overfitting. The final layer uses a softmax function for multi-class classification, suitable for medical datasets where images belong to multiple classes. For clarification, see **Figure 5** and **Figure 6**.

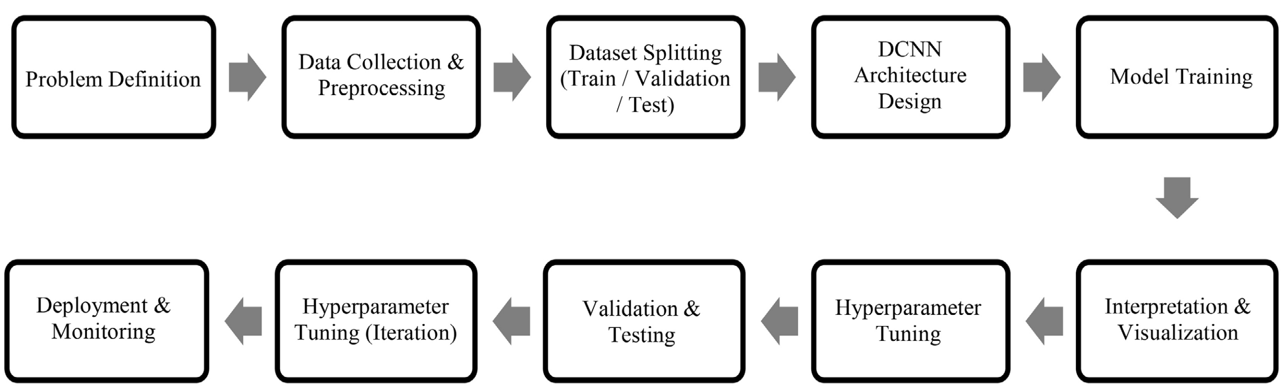

Figure 5. Deep convolutional neural networks overflow.

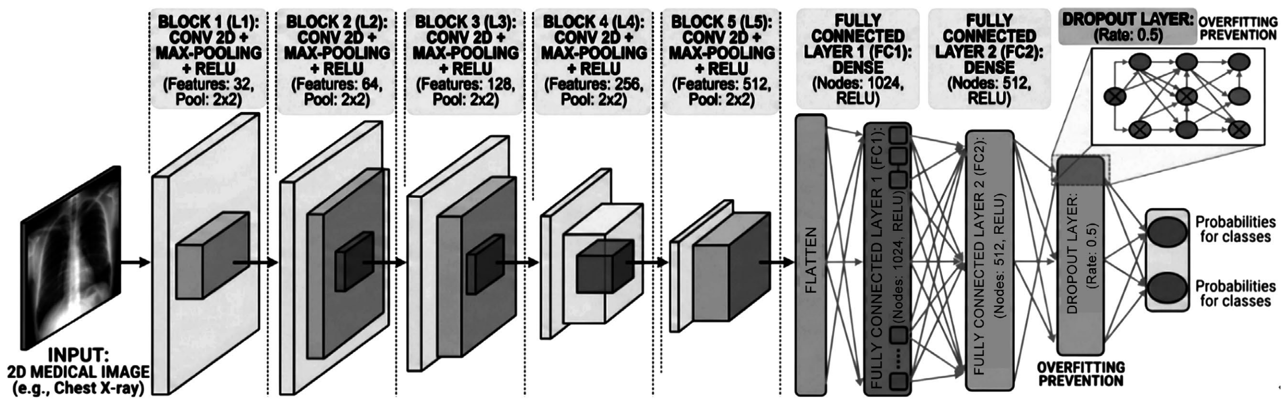

Figure 6. Conceptual deep convolutional neural network model.

To evaluate the proposed framework, a hybrid dataset of medical images was used, comprising chest CT scans and brain MRIs. Due to strict privacy regulations and data-sharing restrictions across most Arab nations, a symmetric, region-exclusive dataset was infeasible; therefore, sample-imbalanced images from local Arab healthcare facilities were combined with images from international repositories, including the NIH and the Medical Segmentation Decathlon. To reconcile this dual provenance and support the paper's claims of regional clinical value, the DCNN model was pre-trained on global data to learn robust features, then fine-tuned via transfer learning on Arab-population data to calibrate it to regional demographics and imaging protocols. This experimental classification setup represents the final phase of our four-part study design, following a literature review, expert consultation, and secure IoT routing evaluation, thereby directly linking secure edge-transmission protocols to optimized, region-specific clinical diagnostics.

4. Deep Convolutional Neural Networks Model

Once the data is successfully transmitted, collected, and formatted, it moves into the preprocessing stage. This involves reshaping the data into a single dimension, normalizing it, and then reshaping it back into two dimensions. Next, the data is standardized to have a distribution centered at zero with consistent variance. Finally, the dataset is split into two parts: one for training the model and the other for testing its performance. The training set can now be represented as

$$D_{train} = \left\{ \left(x_i, y_i \right) \right\}_{i=1}^{m} \tag{1}$$

where $x_i \in \mathbb{R}^{H \times W \times C}$ is the i-th input image (a 2D matrix with channels), $y_i \in \{1, 2, \cdots, K\}$ is the corresponding class label, m is the total number of training samples and H, W, C denote height, width, and number of channels. This framework is built on TensorFlow, making it easy to use. TensorFlow uses the concept of tensors as its primary data representation, with n-dimensional arrays that flow into the layers of the network. A two-dimensional tensor can represent batches and sample features, with the only thing to be determined at the outset being the shape of the input tensors. All the other shapes of the tensors associated with other layers will be automatically deduced from the properties of the corresponding layers. For example, there is no need to specify the exact number of samples when using Keras, since this value will be determined after training starts, as shown in Table 1. When constructing the model, a compact tensor with several rows and columns and a single channel is defined, and the shapes of other tensors, such as the number of neurons in dense layers together with the number of filters in convolutional layers, are automatically derived from those layers' configurations. Each layer extracts pertinent features from the input and converts them into accurate predictions. To start, there is a convolutional layer in which a 3 × 3 kernel slides over the input to generate feature maps. Next, pooling reduces the spatial dimensions of the feature maps without losing key details. Max-pooling selects the maximum value within each region. Pooling reduces the number of parameters, lowers the computational burden, and helps prevent overfitting. The same convolution-pooling process is repeated to further improve feature extraction. This is followed by flattening, which converts the multidimensional feature maps into a single vector. Next, two dense layers extract high-level features. ReLU activation functions are used in the hidden layers, and softmax is applied to the output layer.

Table 1. Keras sequential model with 12 stacked layers.

```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(t_rows, t_cols,1)))
model.add(Conv2D(32, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dense(20, activation='softmax'))
model.compile(optimizer='adam',loss='categorical_crossentropy',
metrics=['accuracy'])
model.summary()
```

The proposed model uses the Adam optimizer, an adaptive learning rate algorithm that combines the benefits of both momentum and RMSProp [40]. While traditional optimizers adjust the learning rate globally, Adam assigns an adaptive learning rate to each parameter by computing the first and second moments of the gradient. As a result, this approach often leads to faster convergence. The rule for updating the parameter θ at iteration t according to Adam, is given by:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}, \tag{2}$$

where, η is the learning rate, ϵ is a small constant for numerical stability, and

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t},\ m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\theta L(\theta_t), \tag{3}$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t},\ v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla_\theta L(\theta_t))^2. \tag{4}$$

Here, $\nabla_\theta L(\theta_t)$ is the gradient of the loss function, m_t and v_t are the first and second moment estimates, and β_1, β_2 are hyperparameters that control the decay rates. A major advantage of the Adam algorithm is its ability to address the vanishing-gradient problem effectively. It does this by adaptively tuning learning rates and updating parameters, thereby accelerating convergence and improving model performance. The ReLU activation function also helps by keeping the gradient nonzero for positive inputs, thereby reducing vanishing gradient issues. This approach contrasts with stochastic gradient descent, where careful tuning of learning rate and momentum parameters is often required. Adam requires hyperparameters $beta_1$ and $beta_2$ that determine the decay rate of the moments. During training, the neural network performs forward and backward passes, and the complete process over the dataset constitutes one epoch. To improve efficiency and save memory, data is divided into small segments called batches. An epoch consists of multiple batches, and in each batch, the Adam optimizer updates the model parameters to minimize the loss. After training is complete, the model can predict labels for unseen data, and accuracy, which measures the correctness of predictions across all predictions, is used as a performance metric. For more information about the formulated architecture, refer to [5]. Below is a Python program that implements the model using the Keras Sequential API. The model uses convolutional layers with ReLU activations and max pooling, followed by dense and dropout layers. During training, the Adam optimizer and categorical cross-entropy loss function are used for this multi-class medical image classification task. Once the predictive model is built, we test it on a different dataset to generate labels for previously unseen healthcare samples. We measure the model's effectiveness by determining its accuracy.

5. Results and Discussion

This study demonstrates the strong potential of integrating secure IoT protocols with DCNNs to improve healthcare in the Arab region. Unlike previous studies that focused separately on medical image analysis or IoT-based remote monitoring, the proposed Arab-region intelligent medical framework combines both technologies within a secure healthcare ecosystem that supports real-time clinical decision-making. The findings show that secure IoT data collection and deep learning analytics provide an integrated approach to disease detection, patient monitoring, and personalized care. A key contribution of this research is its use of healthcare data relevant to the Arab region, whereas many existing deep learning healthcare models are trained on datasets from North America, Europe, or East Asia. Healthcare patterns in Arab countries are influenced by genetic factors, environmental conditions, dietary habits, cultural practices, and a high prevalence of chronic diseases such as diabetes mellitus, cardiovascular issues, obesity, hypertension, and respiratory illnesses. Therefore, models trained on region-specific healthcare data are expected to produce more accurate and clinically meaningful predictions for Arab populations. Integrating secure IoT protocols also increases the framework's practical value. Data from wearable sensors, smart medical devices, and remote monitoring systems are highly sensitive and require strong safeguards to ensure confidentiality, integrity, and availability. The framework's secure communication protocols support reliable patient data transmission while reducing the risks of cyberattacks, unauthorized access, and data tampering. This is especially important in smart healthcare environments, where continuous monitoring generates large volumes of real-time physiological data. Overall, the results suggest that secure IoT infrastructures can enable trusted healthcare data exchange without compromising analytical performance. To maintain a clear focus on deep learning evaluation, we have omitted detailed network performance data here. However, a comprehensive simulation using NS2 revealed that the proposed method effectively reduces packet loss, latency, congestion, and network load, thereby maintaining a stable data flow across the healthcare IoT infrastructure.

The effectiveness of DCNNs in analyzing diverse healthcare data was evident in the experimental results. Unlike traditional machine learning methods that rely heavily on handcrafted features, DCNNs automatically learn hierarchical representations from complex medical datasets. This enables them to identify subtle disease patterns that standard statistical techniques might overlook. By integrating data from various IoT sources, including physiological measurements, medical images, and patient monitoring records, the model uncovers complex relationships among clinical variables, thereby improving diagnostic accuracy. These findings align with recent progress in deep learning, in which convolutional architectures have demonstrated superior performance in healthcare analytics and medical image analysis. The framework also supports personalized medicine within the Arab healthcare sector. Continuous data collection via IoT devices generates dynamic patient profiles that reflect real-time physiological states. When processed by DCNNs, these profiles enable personalized risk assessments, disease progression predictions, and tailored treatment plans. Recognizing patient-specific patterns is especially useful for managing chronic diseases prevalent in Arab countries. Personalized interventions based on real-time data can improve treatment outcomes, reduce hospitalization rates, and optimize healthcare resource use. Another key contribution of this study is its role in preventive healthcare. Early disease detection remains one of the most effective ways to reduce healthcare costs and improve patient outcomes. The proposed intelligent framework continuously monitors patient conditions and detects abnormal patterns before clinical symptoms intensify.

The input layer is the network's starting point, where each node receives a weight. All these weights are adjusted over many training passes (epochs) using all records in the dataset. Before training, some settings must be defined, such as the number of epochs, the number of nodes, and the activation function. The goal after each epoch is to reduce the loss, adjust the weights, and increase accuracy until the entire training process ends. When developing any deep learning model, it is customary to choose VGGNet for its simplicity, satisfactory performance, and ease of transferring its components across different architectures. The Arabic medical data used in this study were obtained from reliable international resources accessible to scientists. Feature extraction and classification are the two major components of the network architecture. They were initially assessed independently before the entire architecture was evaluated. After analyzing the entire architecture, its performance is compared with that of other available approaches. One of the major challenges in dropout prediction for complex medical images is creating reliable representations and developing an efficient feature extractor. Regarding the interpretation and validation of our model in clinical practice, there are various levels, given the immense importance of decision-making in healthcare. Figure 7 provides a framework for interpreting the results of the DCNNs used here. A convergence graph in Figure 8 shows training and validation accuracy across epochs, demonstrating the optimized DCNN's convergence performance.

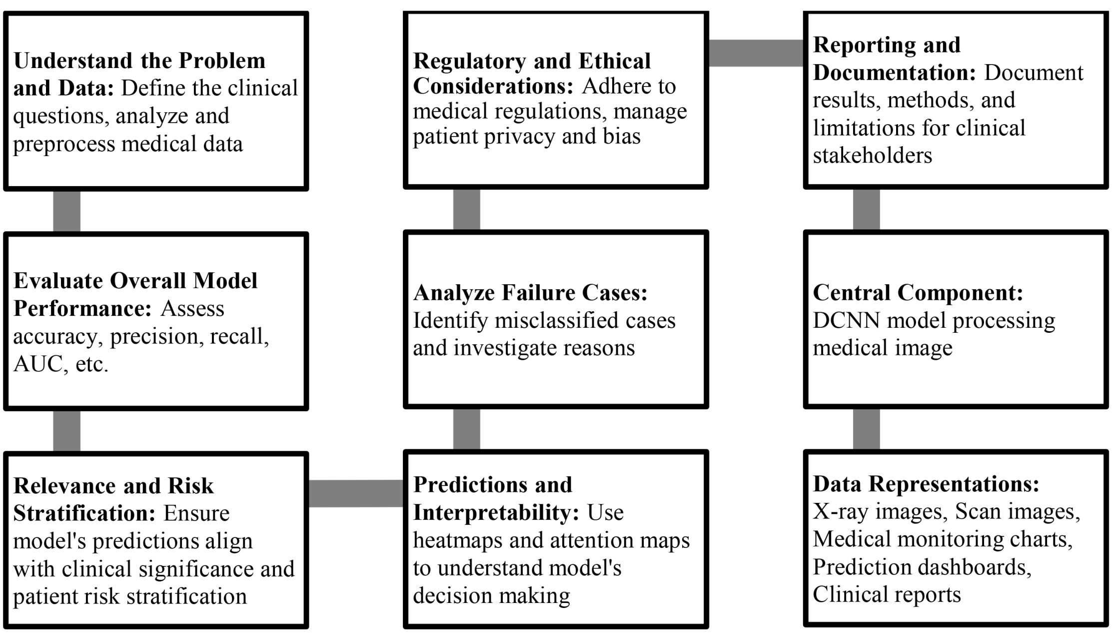

Figure 7. Analyzing the results of a DCNN applied to healthcare data.

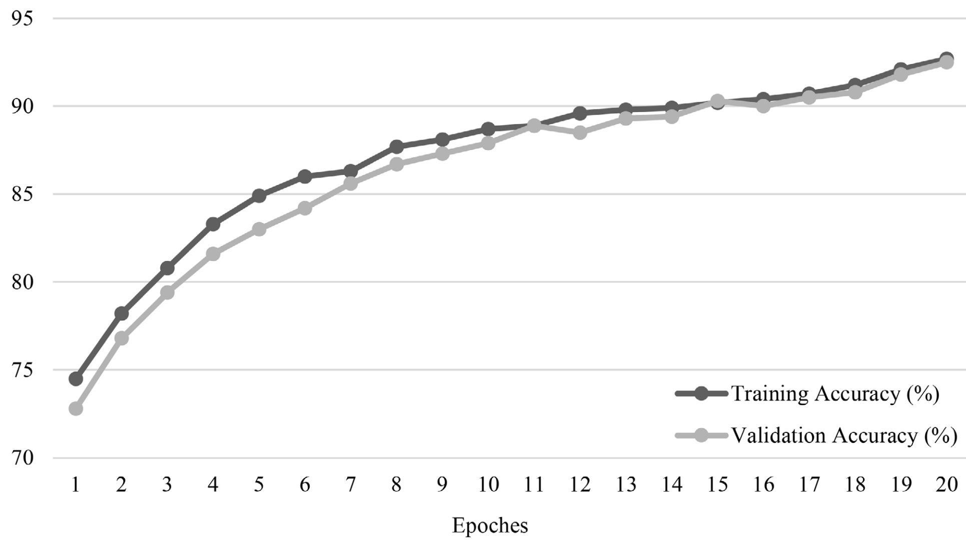

Figure 8. Training vs. validation accuracy curve.

Most research focuses on achieving the highest possible classification accuracy, regardless of the approach used, including several deep learning architectures, while disregarding computational complexity. Despite the relatively small dataset, given the number of images and patients involved in the experiment, the introduced model demonstrates remarkable performance. This model demonstrates its ability to detect cases, and its impressive recall is highly valuable in medical imaging, making it an efficient classifier. The performance metrics for the proposed model are: an average accuracy of 92.5%, precision of 91%, recall of 94%, and an F1 score of 93%. We now compare it with traditional machine learning approaches and report the highest accuracy achieved by each model. SVM achieved about 81% accuracy and a 79.5% F1 score, while KNN performed worse because its performance depends heavily on the quality of high-dimensional features and the noise level in images; it achieved only 78% accuracy and a 76% F1 score. This can be explained by the fact that SVM models handle linear and mild nonlinear boundary conditions, which are insufficient to capture the complexity of features in medical images. By contrast, the LSTM model achieved excellent results, with the highest accuracy of 93% and an F1 score of 91%. However, the presented approach yields similarly satisfactory results and even improves the LSTM algorithm's performance, without compromising precision and recall. The random forest model was found to be equally accurate, with accuracy and F1 score both at 81%. That suggests it performs well with the complexity and heterogeneity of medical features, but still falls short of the suggested model for medical imaging tasks. Compared with contemporary state-of-the-art models, such as CNN-CheXNet, which is based on the DenseNet-121 architecture and detects lung diseases with 88% - 93% accuracy [41], the developed model demonstrates equally reliable performance with less data. **Figure 9** illustrates the false rate (%) achieved by different classification models. The proposed Secure IoT-DCNN model records the lowest false rate, indicating superior predictive reliability. These results highlight the effectiveness of the proposed Secure IoT-DCNN approach in reducing classification errors compared with both deep learning and conventional machine learning.

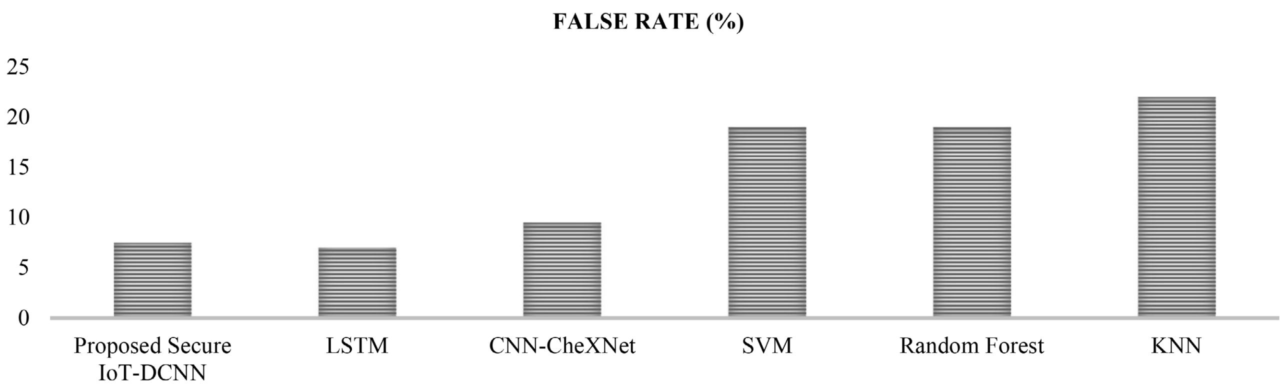

Figure 9. Comparison of false rate (%) across DL and ML models.

We concluded the results and discussion by presenting scalability tests of our deep convolutional neural network framework. The framework scales efficiently as data volume and the number of IoT devices increase. We observed linear improvements in data transfer rate and response time, while resource consumption remained low despite increased computational effort. Overall, the findings validate that combining secure IoT protocols with DCNN-based analytics creates a robust platform for healthcare enhancement. The integration of real-time data collection, secure communication, sophisticated deep-learning analysis, and localized healthcare insights lays a solid foundation for developing next-generation intelligent healthcare systems in the Arab region. Thus, the suggested model demonstrates high efficiency and can be applied to disease detection using AI-enhanced medical images. Future research could investigate integrating blockchain-enabled security, federated learning, explainable artificial intelligence, and large-scale healthcare datasets from multiple Arab countries to enhance transparency, scalability, and the clinical use of intelligent medical systems.

6. Conclusions

The integration of deep learning technologies into IoT systems is expected to improve the effectiveness of health maintenance in the Arab region. By utilizing data from wearable IoT sensors and leveraging the high accuracy of convolutional models for diagnosis, the primary objective of developing an efficient automated system for image interpretation and disease detection is achieved.

On the other hand, beyond computational complexity and high resource consumption, machine learning for analyzing large-scale healthcare data has other limitations, such as limited interpretability, which makes it less efficient in practice. Furthermore, data from various IoT sensors may be noisy, incomplete, and inconsistent due to heterogeneity. Privacy and data security issues also arise from breaches in the IoT infrastructure through which information flows. Standardization and cross-domain interoperability issues pose another limitation for deep learning applications, hindering the integration of diverse IoT systems. Future studies can address these limitations by developing robust models that leverage transfer and multi-task learning. Correspondingly, subsequent research should incorporate other technological approaches, such as Blockchain concepts, to address the limitations observed in the present study.

Acknowledgements

The authors sincerely thank the professional staff of private healthcare facilities in Kuwait for their essential assistance in completing this paper. Their expertise and contributions were invaluable to the study's success. We also extend gratitude to everyone who helped with coordination and administration during this research.

Ethics

This manuscript is an original contribution, and the author declares that no ethical issues are involved.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Taye, M.M. (2023) Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions. *Computation*, **11**, 52.

[2] Sayed, M. and Baker, F. (2018) Thermal Face Authentication with Convolutional Neural Network. *Journal of Computer Science*, **14**, 1627-1637. https://doi.org/10.3844/jcssp.2018.1627.1637

[3] Sayed, M. (2018) Biometric Gait Recognition Based on Machine Learning Algorithms. *Journal of Computer Science*, **14**, 1064-1073. https://doi.org/10.3844/jcssp.2018.1064.1073

[4] Sayed, M. (2018) Performance of Convolutional Neural Networks for Human Identification by Gait Recognition. *Journal of Artificial Intelligence*, **11**, 30-38. https://doi.org/10.3923/jai.2018.30.38

[5] Sayed, M. (2024) Student Progression and Dropout Rates Using Convolutional Neural Network: A Case Study of the Arab Open University. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, **28**, 668-678. https://doi.org/10.20965/jaciii.2024.p0668

[6] Sureshkumar, S., Santhosh Babu, A., Joseph James, S. and Maranco, M. (2025) Deep Convolutional Neural Network Based Archimedes Optimization Algorithm for Heart Disease Prediction Based on Secured IoT Enabled Health Care Monitoring System. *Scientific Reports*, **15**, Article No. 27028. https://doi.org/10.1038/s41598-025-12581-8

[7] Hadji, I. and Wildes, R. (2018) What Do We Understand about Convolutional Networks? arXiv: 1803.08834.

[8] Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2017) ImageNet Classification with Deep Convolutional Neural Networks. *Communications of the ACM*, **60**, 84-90. https://doi.org/10.1145/3065386

[9] LeCun, Y., Bottou, L., Bengio, Y. and Haffner, P. (1998) Gradient-Based Learning Applied to Document Recognition. *Proceedings of the IEEE*, **86**, 2278-2324. https://doi.org/10.1109/5.726791

[10] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., *et al.* (2015) Going Deeper with Convolutions. 2015 *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Boston, 7-12 June 2015, 1-9. https://doi.org/10.1109/cvpr.2015.7298594

[11] Simonyan, K. and Zisserman, A. (2014) Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv: 1409.1556.

[12] Szegedy, C., Ioffe, S., Vanhoucke, V. and Alemi, A. (2017) Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. *Proceedings of the* 31*st AAAI Conference on Artificial Intelligence* (*AAAI*-17), San Francisco, 4-9 February 2017, 4278-4284.

[13] Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q. (2017) Densely Connected Convolutional Networks. 2017 *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Honolulu, 21-26 July 2017, 2261-2269. https://doi.org/10.1109/cvpr.2017.243

[14] He, K.M., Zhang, X.Y., Ren, S.Q. and Sun, J. (2016) Deep Residual Learning for Image Recognition. 2016 *IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Las Vegas, 27-30 June 2016, 770-778. https://doi.org/10.1109/cvpr.2016.90

[15] Aldogiher, A. and Halim, Y.T. (2025) Customer Engagement in Digital Health Transformation as Strategic Change: Evidence from Saudi Arabia's Vision 2030. *Sustainability*, **17**, Article 8468. https://doi.org/10.3390/su17188468

[16] Unicef Lebanon (2026) National Digital Health Transformation Strategy 2025-2030. https://www.unicef.org/lebanon/reports/national-digital-health-transformation-strategy

[17] Qasrawi, R., Tayyem, R., Thwib, S., Issa, G., Amro, M., AbuGhoush, R., *et al.* (2025) Digital Health Determinants & Divide in the Arab World: A Cross-Sectional Study. *PLOS ONE*, **20**, e0338299. https://doi.org/10.1371/journal.pone.0338299

[18] Sharma, K. (2026) From Crisis to Catalyst: The Middle East's Telehealth Transformation. https://www.jll.com/en-ae/insights/from-crisis-to-catalyst-the-middle-easts-telehealth-transformation

[19] Tan, C., Yuan, Z., Xu, F. and Xie, D. (2025) Optimized Feature Selection and Deep Neural Networks to Improve Heart Disease Prediction. *Journal of Imaging Informatics in Medicine*, **39**, 908-925. https://doi.org/10.1007/s10278-025-01435-4

[20] Wang, J., Zhu, H., Wang, S. and Zhang, Y. (2021) A Review of Deep Learning on Medical Image Analysis. *Mobile Networks and Applications*, **26**, 351-380. https://doi.org/10.1007/s11036-020-01672-7

[21] Yang, H., Wang, Z., Liu, X., Li, C., Xin, J. and Wang, Z. (2023) Deep Learning in Medical Image Super Resolution: A Review. *Applied Intelligence*, **53**, 20891-20916. https://doi.org/10.1007/s10489-023-04566-9

[22] Isobe, Y., Teramoto, A., Morita, F., Saito, K. and Fujita, H. (2022) Fully Automated Electronic Cleansing Using CycleGAN in Computed Tomography Colonography. *Applied Sciences*, **12**, Article 10789. https://doi.org/10.3390/app122110789

[23] Al Kuwaiti, A., Nazer, K., Al-Reedy, A., Al-Shehri, S., Al-Muhanna, A., Subbarayalu, A.V., *et al.* (2023) A Review of the Role of Artificial Intelligence in Healthcare. *Journal of Personalized Medicine*, **13**, Article 951. https://doi.org/10.3390/jpm13060951

[24] Shamshirband, S., Fathi, M., Dehzangi, A., Chronopoulos, A.T. and Alinejad-Rokny,

H. (2021) A Review on Deep Learning Approaches in Healthcare Systems: Taxonomies, Challenges, and Open Issues. *Journal of Biomedical Informatics*, **113**, Article 103627. https://doi.org/10.1016/j.jbi.2020.103627

[25] Bhatt, C., Kumar, I., Vijayakumar, V., Singh, K.U. and Kumar, A. (2021) The State of the Art of Deep Learning Models in Medical Science and Their Challenges. *Multimedia Systems*, **27**, 599-613. https://doi.org/10.1007/s00530-020-00694-1

[26] Li, L., Wang, X., Hu, W., Xiong, N.N., Du, Y. and Li, B. (2020) Deep Learning in Skin Disease Image Recognition: A Review. *IEEE Access*, **8**, 208264-208280. https://doi.org/10.1109/access.2020.3037258

[27] Dave, T., Athaluri, S.A. and Singh, S. (2023) ChatGPT in Medicine: An Overview of Its Applications, Advantages, Limitations, Future Prospects, and Ethical Considerations. *Frontiers in Artificial Intelligence*, **6**, Article 1169595. https://doi.org/10.3389/frai.2023.1169595

[28] Salman, I.M., Ameer, O.Z., Khanfar, M.A. and Hsieh, Y. (2025) Artificial Intelligence in Healthcare Education: Evaluating the Accuracy of ChatGPT, Copilot, and Google Gemini in Cardiovascular Pharmacology. *Frontiers in Medicine*, **12**, Article 1495378. https://doi.org/10.3389/fmed.2025.1495378

[29] Abujassar, R.S., Sayed, M. and Yaseen, H. (2023) A New Algorithm to Enhance Security against Cyber Threats for Internet of Things Application. *International Journal of Electrical and Computer Engineering*, **13**, 4452-4466. https://doi.org/10.11591/ijece.v13i4.pp4452-4466

[30] Ksibi, S., Jaidi, F. and Bouhoula, A. (2023) A Comprehensive Study of Security and Cyber-Security Risk Management within E-Health Systems: Synthesis, Analysis and a Novel Quantified Approach. *Mobile Networks and Applications*, **28**, 107-127. https://doi.org/10.1007/s11036-022-02042-1

[31] Singh, R.P. and Dixit, M. (2015) Histogram Equalization: A Strong Technique for Image Enhancement. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, **8**, 345-352. https://doi.org/10.14257/ijsip.2015.8.8.35

[32] Kim, Y.T. (1997) Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization. *IEEE Transactions on Consumer Electronics*, **43**, 1-8. https://doi.org/10.1109/30.580378

[33] McCaffrey, J. (2014) Understanding Neural Network Batch Training: A Tutorial. Visual Studio Magazine. https://visualstudiomagazine.com/articles/2014/08/01/batch-training.aspx

[34] Kale, K. and Pandey, D.R. (2024) Data Pre-Processing Technique for Enhancing Healthcare Data Quality Using Artificial Intelligence. *International Journal of Scientific Research in Science and Technology*, **11**, 299-309. https://doi.org/10.32628/ijsrst52411130

[35] Salmi, M., Atif, D., Oliva, D., Abraham, A. and Ventura, S. (2024) Handling Imbalanced Medical Datasets: Review of a Decade of Research. *Artificial Intelligence Review*, **57**, Article No. 273. https://doi.org/10.1007/s10462-024-10884-2

[36] Glorot, X. and Bengio, Y. (2010) Understanding the Difficulty of Training Deep Feedforward Neural Networks. *Proceedings of the* 13*th International Conference on Artificial Intelligence and Statistics* (*AISTATS*), Sardinia, 13-15 May 2010, 1-8.

[37] Rohrer, B. (2016) How Do Convolutional Neural Networks Work? Data Science and Robots Blog. https://brohrer.github.io/how_convolutional_neural_networks_work.html

[38] Nielsen, M. (2017) Improving the Way Neural Networks Learn.

http://neuralnetworksanddeeplearning.com/chap3.html

[39] Mahmud, R., Pallewatta, S., Goudarzi, M. and Buyya, R. (2022) An Extended iFogSim Simulator for Mobility, Clustering, and Microservice Management in Edge and Fog Computing Environments. *Journal of Systems and Software*, **190**, Article 111351. https://doi.org/10.1016/j.jss.2022.111351

[40] Reyad, M., Sarhan, A.M. and Arafa, M. (2023) A Modified Adam Algorithm for Deep Neural Network Optimization. *Neural Computing and Applications*, **35**, 17095-17112. https://doi.org/10.1007/s00521-023-08568-z

[41] CheXNet: CNN for Pneumonia Detection. Emergent Mind. https://www.emergentmind.com/topics/chexnet