A Comprehensive Sophisticated Pattern Analysis Framework to Scan Cancer Cells by Using an Intelligent IoT

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Abstract:

The fusion in between the of the Internet of Things (IoT) and dvanced machine learning algorithms enables a: new way of innovat tion in healthcare.One such application is cancer diseases detection with CNNs, which are very well at pattern discovery in medical images. Extensive research is currently underway in the field of oncology to screen, prevent and treat cancer disease because it is life-threatening and second leading cause of deaths in the world. According to the survey various caner types have been identified but continuous monitoring of cancer cells is missing to enhance the patient outcome. Continuous monitoring and Early detection of cancer are essential to enhancing patient outcome. This research presents an integrated system leveraging Deep Learning-based Cancer Monitoring and a Smart IoT Simulation to automate blood sample analysis and enhance diagnostic accuracy. Histological image dataset has been used to compare result. Finally, this paper presents a novel approach that integrates IoT technology with the power of CNN for Continuous cancer disease monitoring. By harnessing the potential of this intelligent IoT-CNN system, healthcare institutions can effectively combat cancer by enabling timely diagnosis and personalized treatment strategies.

Keywords: Deep learning (DL), Internet of Things (IoT), Cancer, DNA

1.Introduction

Cancer is a challenging, destructive disease which is affecting millions of people globally. Early and precise detection of cancer cells is crucial for enhancing the diagnosis in patients while the timely response elevates the probability of successful treatment. Conventional methods of cancer detection rely on pathologists examining tissue samples by hand, a process that's not only time-intensive and subjective but error-prone. It has given the challenges with such task, the researchers started to use advanced techniques (e.g., deep learning) in order to increase the accuracy and sensitivity in detecting cancer cells. DL is a sub-discipline of AI which aims at learning and training artificial neural networks to predict from large datasets. In computer science, for instance, it has proved highly successful for many tasks. Vision, language processing, and medical applications. Deep learning has recently been a rising power in the development of a number of techniques for automating and enhancing the accuracy of cancer diagnosis in the setting of cancer cell detection.The basic idea behind DL for cancer cell detection is to use neural networks to learn relevant features from images or other data types automatically.For cancer diagnosis, deep learning models can learn to identify structure and anomalies in medical images including histopathologystain, radiology images and even biochemical analysis.

Currently, most researchers are attempting to create novel and advanced tools for patient health monitoring. Identifying the correct disease and timely treatment required for cancer patients is critical. Many automated techniques focused on detecting cancer cells using online datasets [1]. Deep Learning (DL) is most commonly used to detect cancer cells in datasets. Several types of cancer are the leading cause of death in patients [2]. Breast cancer is a leading cause of mortality worldwide. Early detection of cancer cell may prevent the mortality and improve the survival.

Early research uses available technology to improve cancer detection in its early stages [3]. DL algorithms are increasingly detecting cancer in its early stages. The Internet of Things (IoT) is a technology that can detect abnormal tumors in the human body [4]. It's prevalent to diagnose Tumors commonly used to diagnose cancer. Some tumors are transformed into cancers, while others are not. Combining IoT and DL algorithms allows for more accurate and improved detection of cancer cells as well as continuous monitoring of cancer cell growth. In this paper, an integrated framework connected with smart IoT and CNN used to is developed to detect tumors, tumor growth, tumor size, and abnormalities in tumors.

2. Literature Survey

Nisar et al. [6] discussed various DL algorithms for detecting several diseases-belongs in different sets of humans. Norgeot et al. [7] introduced advanced healthcare systems that combine deep learning. Ravi et al. [8] introduced the advanced DL health analysis system that helps find better models to overcome various issues in healthcare systems. S. Sharma et al., [9] introduced a more popular ML algorithm that detects breast cancer detection. The ML algorithm's performance was tested using the Wisconsin Diagnosis Breast Cancer dataset and was refined. Md. Milon Islam et al., [10] compared the five ML algorithms to detect breast cancer detection by using the Wisconsin Breast Cancer dataset. From these algorithms, artificial neural networks (ANNs) achieved better results based on accuracy, precision, and F1 scores of 98.57%, 97.82%, and 0.9890. M. Gurbina et al., [11] introduced the detection and classification of brain tumors by using wavelet transforms and SVM. The proposed approach obtained accurate results compared with existing models.

K. Barhanpurkar et al., [12] introduced the Modified Fusion Convolution Neural Network (MFCNN) used to detect sleep apnea which is analyzed from the ECG data. This should be detected in the early stages otherwise this may affect the respiratory system and may convert to lung cancer. The proposed DL model analyzed the health conditions of the patients and finds the accurate detection of the status of the disease. A. Naeem et al., [13] discussed various existing and popular algorithms that are most widely used to detect melanoma and analyze the performance in terms of detection rate. SK Shukla et al., [14] introduced the Integrated AI-based IoT model that detects breast cancer cells from the given dataset. The proposed system analyzes the size of the cancer cells and the growth of cancer cells. The proposed approach also analyzes the risk of the cancer and temperature of the patient. Based on the temperature cancer cells may be increased and the density of the breast size and analyze the development of cancer cells. Osama Rehman et al., [15] proposed a new prototype called as Patient Side Unit (PSU) which is a physical wrist band. This system reduces expenses and gains the quality of services.

Chapala et al. proposed a new approach that detects cancer cells using lung computed tomography (CT) images.

The proposed approach finds the abnormalities present in the lungs and detects the abnormal cells present in the lungs. Siddhant Salvi et al., [17] proposed a new approach to detect breast cancer cells based on the tumor types. This approach is also used to detect the early stages of tumors.

3. Proposed Model

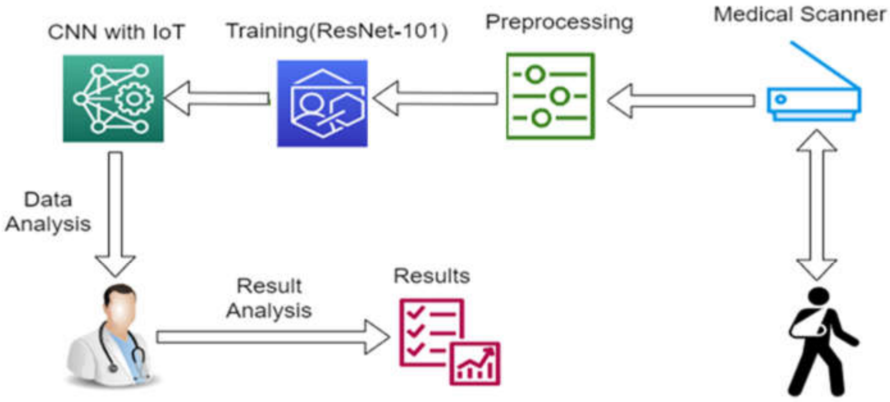

Figure 1: System Architecture

The combination of Internet of Things (IoT) technology and advanced medical diagnostics has transformed healthcare by allowing real-time monitoring, diagnosis, and treatment of various medical conditions. The proposed approach uses IoT to detect cancer cells, providing a cutting-edge approach to early cancer diagnosis and improved patient outcomes. The proposed system combines smart devices with data analytics.Machine learning techniques recognize cancer cells with precision. They also do so with ease and speed. TheData acquisition process and also components of that smart IoT system are investigated by the approach that was proposed.Data analytics as well as machine learning both play a role with potential challenges. This revolutionary approach presents also several prospects regarding cancer detection approach. Early detection is important because cancer is a leading cause of mortality worldwide and for successful treatment outcomes. Traditional cancer detection methods often rely on invasive procedures, leading to delayed diagnosis and reduced survival rates. The advent of IoT technology presents an opportunity to revolutionize cancer detection by providing non-invasive, real-time monitoring and analysis.

3.1 Components of the Smart IoT System:

The proposed smart IoT system for cancer cell detection consists of three main components:

Sensors and Devices: Biochemical and imaging sensors are integrated into wearable devices, smartphone apps, and other smart gadgets. These sensors collect data such as blood parameters, tissue characteristics, and imaging data.

Data Communication: IoT enables seamless data transmission from sensors to a central data repository or cloud platform. This facilitates real-time data analysis and accessibility for medical professionals.

Data Analytics and Machine Learning: Machine learning along with advanced data analytics techniques

Algorithms collect data then process it. Also they recognize possible cancer signs along with trends and anomalies.

3.2 Data Acquisition Process:

Biological Samples: Blood, urine, tissue samples, and imaging data (X-rays, MRIs, etc.) are collected from patients using IoT-enabled devices.

Data Transmission: The gathered data is securely sent to a platform based in the cloud for analysis.

Data Preprocessing: Raw data is preprocessed to eliminate noise and irrelevant information, which is used in the followed step, which is grouping and normalizing.

Feature Extraction: Salient features are extracted from preprocessed data to train the

machine learning models.

3.3 Role of Data Analytics and Machine Learning:

Pattern Recognition: Models of trained machine learning are what recognize patterns that are associated with cancer cells. These models learn using historical data, so accuracy improves over time.

Anomaly Detection: ML algorithms identify deviations from normal cell behavior, indicating potential cancerous activity.

Real-time Monitoring: Continuous data analysis allows for real-time monitoring of patients, enabling prompt intervention when anomalies are detected.

3.4 Denoising Auto-Encoder

A denoising autoencoder is an artificial neural network that trains the network to remove noise from corrupted input samples to learn efficient data representations. Autoencoders are generally a neural kind of network which is created for unsupervised learning, so it learns a tight depiction of input data in an unsupervised manner. Denoising autoencoders function by injecting noise into the input data.Then the autoencoder learns to reproduce the initial, undamaged data. It has to lean on the why the initial input of the noisy version is reconstructed through the use of underlying patterns that force the network to The data do allow for learning of meaningful features. Those features learned now will be strong.

The formula for a denoising autoencoder can be broken down into several components:

Encoder Function (Encoding):

The encoder function maps the input data (noisy data) to a lower-dimensional representation called the "encoded" or "latent" representation.

Mathematically, the encoder function can be represented as:

$$h = f_{enc}(x + \in)$$

Where:

h is the encoded representation.

f_{enc} is the encoder function.

x is the noisy input data.

$\in$ is the added noise.

Decoder Function (Decoding):

With the encoded representation, original clean data is reconstructed by the decoder function. Mathematically, the decoder function can be represented as:

$$\hat{x} = f_{dec}(h)$$

$\hat{x}$ is the reconstrued data.

f_{dec} is the reconstrued data.

h is the reconstrued data.

Loss Function:

In training the denoising autoencoder, we aim to make the difference between the reconstructed data (1-x) as small as possible for all vectors in the dataset() and raw data free from any contamination ()

One common choice for the loss function is the mean squared error (MSE) between the reconstructed and original data:

$$\text{Loss} = \frac{1}{N}\sum_{i=1}^{N} ||x_i - \hat{x}_i||_2^2$$

Where:

N is the number of training samples

x_i is the original data for the $i-th$ sample.

$\hat{x}_i$ is the reconstruction data for the $i-th$ sample.

3.5 RESNET-101 for training:

ResNet-101, an abbreviation of Residual Network-101, is a type of deep convolutional neural network, proved to be better in handling the challenges in training deep networks. The core innovation ofResNet-101 is the residual blocks, which make it possible for the network to learn the residual functions rather than the actual representations by the underlying layers which recognizing the hoped-for underlying mechanisms in themselves. It helps to alleviate the vanishing gradient problem and allows for training much deeper networks. The architecture's potential to capture the complex features across multiple scales makes it well-suited for detecting cancer cells in histopathological images. Histopathology images: Histopathological images are key to understanding the cellular composition of tissue and is important for cancer sontata. Detecting cancer cells within these images involves identifying irregularities, aberrant cell morphology, and patterns indicative of malignancy. Traditional methods rely heavily on manual inspection by pathologists, making the process both time-consuming and subjective. Deep learning approaches, such as utilizing ResNet-101, can potentially automate this process, resulting in faster and more consistent cancer cell detection.

In this study, we employ the ResNet-101 architecture for cancer cell detection. The network is pre-trained on a large dataset to capture generic image properties and patterns. Fine tuning is achieved using a dedicated dataset, comprising of histopathological images with cancer cell annotations. By adapting the network's parameters to the specific task, we aim to enhance its ability to recognize the nuanced features associated with cancer cells.

3.6 Convolutional Neural Network (CNN) for analyzing the cancer tumors

They are of the architectural style: Convolutional layers. Convolutional layers are mainly used on images to detect features CNNs learn a feature for every shift of the kernel on the image. The nearby structures of

an image is taken over all neurons of the Convolutional layer. The weights of each neuron are shared across

nodes of the Convolutional layers to ley them to obtain the same features of the input image channels.

A DCNN is taught by inputting such to the first layer and letting it perform computations to extract features and output results. Once this result is computed, the error is computed, which is backpropagated through the layers across the network. At every stage of the model, parameters are adjusted to further reduce error. This iterative workflow moves on to the data itself, and the model gets better as it goes. The training of the CNN is an iterative process with different layer passing input and parameters being updated until the model converge.There are three key layers to build a CNN architecture: convolutional layer, fully connected layer

,pooling layer. In practice, a deep CNN architecture is constructed by stacking multiple such layers in one -side.The CNN with 2 feature-stage CNN with two feature stage architecture.

The computational basis of a CNN is a feature map extracted from an image or picture. We feed the image to the convolution layer – which in turn scans over the image using a tiny kernel. For all pixels of an image, a dot product is calculated with a kernel (or filter). A kernel or convolution kernel is also any setting of shared weights. Any configuration of shared weights is a kernel (also called convolution kernel). Having said the above, If the size of an image is 512 * 512, then the kernel or filter of such image could be (3 * 3),b(5 * 5), or (8 *8) and every neuron in current layer is connected to these filters, or to this part of the image in the previous layer if and only if it is CNN.

$$(I * K)(x, y) = \sum_{i} \sum_{j} I(x + i, y + j) \cdot K(i, j) \qquad (1)$$

Where I is the input image, K is the filter/kernel, and, x, y are pixel coordinates.

ReLU Activation:

$$f(a) = \max(0, a) \qquad (2)$$

Categorical Cross-Entropy Loss:

$$L(y, \hat{y}) = -\sum_{i} y_i \cdot \log(\hat{y}) \qquad (3)$$

Where y is the true label distribution and $\hat{y}$ is the predicted distribution.

On doing so, the Convolutional kernel is able to identify that feature of the image which is visible on the feature map. Both reduce computational demands and achieve a range of hierarchical levels of image features (combinations of convolution-operation blocks are succeeded by a pool-operation block, analogous to the work flow of simple and complex cells in the striate cortex. The process of the max-pooling layer reduces the size of the image while identifying the most relevant feature and creating a feature map, for each input image.

When applying max pooling operation, low-level feature values are thrown away, while high-level feature values are maintained corresponding in the feature vector. Thus max pooling also be used to improve the translation invariance.

Between two Convolutional layers you can add a pooling layer Pooling layers: where images are reduced in size between the convolutional layers. So, its reduces the Parameters and computational resources of neural network and it effectively prevent the over-fitting to a great extent. Pooling (sub sampling) S i is done independently on each depth slice of the input.

The pool operator resizes an image's input along its width and height. In pooling, the max function returns the maximum value of the pixel in a window [14][15]. Mathematically the pooling layer represented as

$$x_{11}, x_{12} \dots .. x_{1,n} \qquad (4)$$

$$x_{21}, x_{22} \dots .. x_{2,n} \qquad (5)$$

$$x_{m1}, x_{m2} \dots .. x_{m,n} \qquad (6)$$

The final output of the pooling layer is-

$$P = \max(R) \qquad (7)$$

Finally, the pooling layer summarizing an input by partitioning each data segment belonging to the input into disjointed rectangular regions and then selecting a maximum value from amongst each of the regions of the data segment for representing that portion of data in a pooled output.

Neurons in the \(l\)-th fully conneted layer have their activation for any single input calculated by matrix-multiplying the activations of all nodes at layer (l-1) and then adding some offset value (bias). The algorithm is, it has this final fully connected layer that goes out for the net output and the final classification and that's where it makes it's final classification.Although this statement would not be universally true, if every neuron of the last layer is connected to every neuron of. For instance, suppose you have a previous layer with "n" neurons and want to connect it to a fully connected layer with "m" neurons. Each neuron in the last layer is linked to each neuron in the fully connected layer, and the link carries a weight. Each neuron's output in the fully connected layer can be calculated as follows:

$$\text{output neuron}_i = \text{Activation function}(\text{WeightedSum}_i + \text{Bias}_i) \qquad (8)$$

Bias_i is the sum of the prior inputs from the previous layer and corresponding weights for neuron

"i," Bias_i is a bias term added to the weighted sum before it is passed through the activation function.

Output Layer: For the given task (e.g., binary classification of cancer cell into malignant/benign), the dense layers would generate output layer having number of neurons as needed.The probability is commonly projected through a softmax activation function for classification.

3.7 Back propagation

Like multilayer perceptrons, CNN uses back-propagation to minimize error in the presence of unknown weights W [16] [17]. The gradient descent algorithm minimizes error/cost function in every iteration The learning rate tells us how long do we need to calculate the lower loss. The algorithm does not converge while the learning parameter is too large, and the algorithm would consume a lot of time for linking the branch.It is therefore challenging to find the best learning rate.

4. Dataset Description

The tumor images and health analysis data are collected from the IoT sensors and Images collected from DLSR camera. Total images are 100 images and sensors data is 1000 health conditions data. This data is collected from 10 patients for the time of 10 days. Using confusion matrix the model performance is analyzed. Performance check is done using by measuring accuracy,precision, recall, f1-score.

Accuracy (Acc): Accuracy represents how many of the predicted positive values were actually positive. Actual and predicted values are correct. Below is the formula used to represent it.

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}}$$

Precision (P): From all positive peaks predicted the following correct ones will have to be measured.

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

Recall (R): Estimating the total positives under real positive cases

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

F1-Score: The F1-score is the harmonic average of precision and recall of a system, expressed formally. Could it be roughly approximated as:

$$\mathrm{F1} - \mathrm{Score} = \frac{2 \text{ x } [(\mathrm{Precision} \text{ x } \mathrm{Recall})]}{(\mathrm{Precision} + \mathrm{Recall})}$$

Parameters	CNN	IoT with CNN
Accuracy (Acc)	94.34	99.12
Precision (P)	92.1	99.67
Recall (R)	93.34	98.34
F1-Score	95.1	99.56

Table 1: Performance of DL model CNN and Integrated Model IoT and CNN

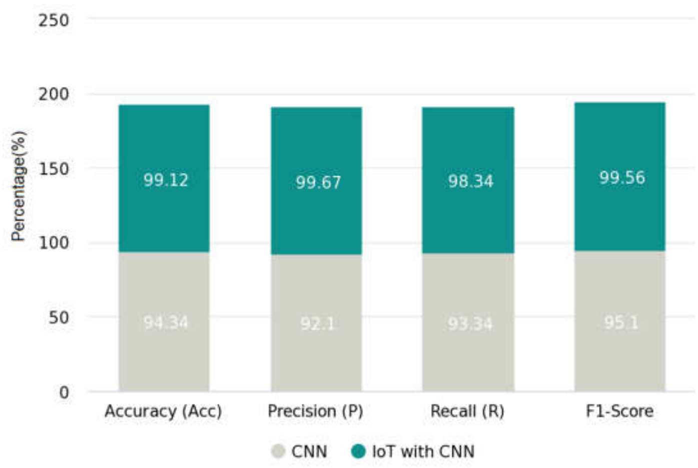

Figure 2: Competition between CNN and CNN with IoT

5. Conclusion

The integration of CNNs with IoT technologies for detecting cancer cells has shown remarkable promise in achieving high accuracy and efficiency in early diagnosis. This innovative approach combines the power of deep learning algorithms with the seamless connectivity and data-sharing capabilities of IoT devices, resulting in a robust system that can revolutionize cancer detection and ultimately improve patient outcomes. Using CNNs, which are adept at learning intricate patterns and features from medical imaging data, this integrated system can effectively analyze histopathological images, radiological scans, or other relevant medical images. The CNNs can automatically detect subtle abnormalities, anomalies, or patterns associated with cancer cells that might be difficult for human experts to identify consistently. The learning process of CNNs can be continuously enhanced with more data, leading to improvements in accuracy over time. IoT devices enhance the potential of this system with the implementation of real-time data collection, transmission, and processing. IoT-enabled devices, such as connected microscopes, sensors, and medical imaging devices, can gather data from various sources, including remote clinics and healthcare facilities. This data can be securely transmitted to a centralized cloud or on-premises servers for processing by CNNs. The results can then be disseminated to healthcare professionals, allowing for timely and informed decision-making. Finally, combining CNNs with IoT technologies offers a promising avenue for advancing cancer detection accuracy and efficiency Using the power of deep learning as well as real-time data collection, this system may transform cancer diagnosis and create a future with less patients suffering and more efficient healthcare industry. Continued research, development, and collaboration between medical experts, AI practitioners, and IoT specialists will be crucial in fully realizing the transformative impact of this approach.

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