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An IoT and RNN Based Synergistic Framework for Diagnosis of Malignant Cells

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Abstract:

Cancer is second leading cause of morbidity and mortality in the present world. Early detection and prediction of uptake of cancer cells is important for patient care and can improve the chances of cure. Recent work has Integrated the IoT and Deep Learning models acts as a promising approach to diagnosis cancer early. According to this research a new model to predict early malignant cells diagnosis by using Internet of things (IoT) and an optimal deep learning approach. The proposed system combines the strengths of IoT in data collection and connectivity with the capabilities of deep learning for data analysis. The integration of these two technologies enables real-time monitoring and analysis of relevant physiological and biological data, facilitating early cancer detection. The key components of this system include sensor devices capable of monitoring vital signs, genetic markers, and other health-related data, which are connected to a central IoT platform. The collected data is then processed and analyzed by an optimized deep learning model. The Recurrent Neural Networks (RNN) model is fine-tuned and optimized to accurately identify early signs of cancer cells from the data, which can include anomalies, biomarkers, or other indicators. optimizing for feature selection, hyper-parameter optimization and model architecture design to improve cancer cell prediction accuracy. The algorithm is also based on adaptive learning to take into account new data and changing cancer profiles. In addition to early prediction, this system can provide personalized health recommendations and alerts to both patients and healthcare professionals. it holds promise to influence the cancer burden by facilitating early interventions and personalized therapies. The proposed model has good potential for early prediction of cancer cells and may result in better patient outcomes and lower healthcare costs. It highlights the synergy of IoT and deep learning as a promising duo in health care and disease management. This system still needs more research and development to prove its effectiveness and be included in clinical routine.

Keywords: Internet of Things (IoT), Deep Learning, Novel Framework, Recurrent Neural Networks (RNN).

1. Introduction

The use of IOT sensors for detecting cancer cells is such a novel concept that merges medical diagnosis with new technology. Early cancer detection and monitoring can be one of the major applications of IoT. Biological sensors biological sensors can be combined with sensors customized to detect cancer biomarkers. These sensors can be designed to monitor blood, urine, or tissue samples for the presence of abnormal cells, proteins, or genetic mutations. For example, biosensors can be used to detect cancer-related markers such as CTCs (Circulating Tumor Cells) or specific cancer-related DNA. Wearable IoT such as smart watches and patches also may continuously monitor autonomic signs, like skin conductivity, body temperature and heart rate for detecting subtle symptoms that could be signs of cancer or cancer treatment side effects. IoT-connected medical imaging equipments (e.g., MRI and CT) can acquire images and communicate images to medical facilitator in real-time, which helps recognize and monitor the tumour at early stage. IoT sensors can be embedded in medical equipment, such as endoscopes or catheters, to provide real-time information to surgeons during procedures, helping them detect and remove cancerous tissue more accurately. Patients with cancer can be provided with IoT-connected devices to monitor their condition from home. These devices can measure vital signs, side effects of treatment, and overall well-being. The data can be communicated to medical facilitator for remotely monitoring. IoT can facilitate telemedicine services, allowing patients to consult with oncologists and other healthcare professionals remotely. They can share data collected from IoT sensors, discuss symptoms, and receive treatment recommendations without needing to visit a healthcare facility. IoT sensors can help in tracking patients' movements and environmental factors that may contribute to cancer risk. This information can be utilized to find possible environmental causes or suggest lifestyle changes to reduce cancer risk. IoT devices can be programmed to send alerts to patients, caregivers, or healthcare providers when specific conditions or anomalies are detected, ensuring timely responses and interventions. Since healthcare data is sensitive, it's crucial to ensure strong encryption and cybersecurity measures to protect patient information when using IoT sensors in a medical context. Use of IOT sensors in cancer detection and monitoring could not only lead to earlier diagnosis, it can also improve patient care, and save healthcare systems from much burden. Yet, it involves drawbacks, including issues on information security and privacy; regulation compliance and requirement of an extensive clinical validation. This will require a concerted effort by physicians and IoT developers, as well as regulatory bodies, in order to provide a safe and efficacious application of these systems.

Deep learning (DL has a vital position in medical image analysis, especially in cancer cell detection. It could transform the diagnosis and treatment of many types of cancer. Cancer constitutes the second most common reason of mortality globally, with early diagnosis being key to successful treatment. Current cancer detection techniques, such as biopsies and manual reading of medical images, tend to be slow, subjective, and even error-prone. Deep learning, a branch of artificial intelligence, appears to be a promising response to these problems. DL models (e.g., CNNs and RNNs) have shown great potential in automatic representation learning of complex patterns and features from medical images (such as X-ray, MR image, CT images, histopathology slides).These models can analyze vast amounts of data, learning to recognize subtle irregularities in tissues or cells that may indicate the presence of cancer. DL algorithms can process large datasets quickly, reducing the time required for diagnosis. This can be crucial in critical cases where prompt treatment is essential. Unlike human examiners, deep learning models provide consistent results regardless of fatigue or variations in expertise, helping to standardize the diagnostic process. DL can detect cancer at an earlier stage when it is more treatable, potentially having a lifesaving impact and minimizing the requirement for surgical interventions. It can help tailor treatment plans by analyzing individual patient data, contributing to the emergence of precision medicine in cancer care. It also aids in cancer research by facilitating the analysis of large-scale genomics and proteomics data, which can uncover novel biomarkers and therapeutic targets. Finally, deep learning is a powerful tool for the diagnosis of cancer cells, offering the possibly to improve the accuracy, speed, and consistency of disease diagnosis and treatment. As technology progresses, we anticipate that deep learning is going to have a more pronounced weight on cancer in patient care, and ultimately on the global burden of cancer.

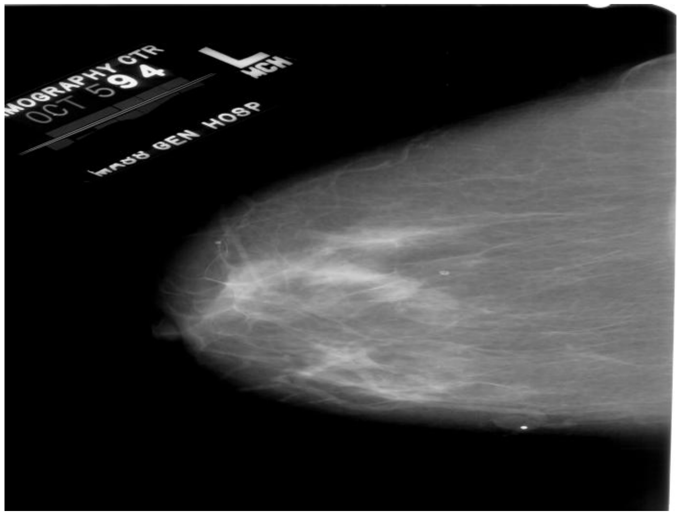

Figure 1: Sample Breast Cancer Image

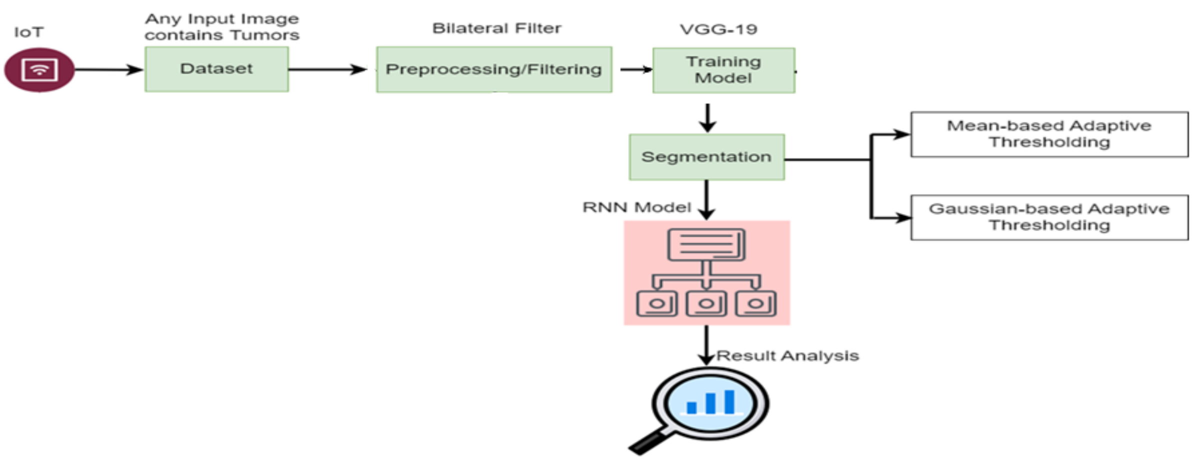

Figure 2: Final Architecture of Proposed Approach

2. Literature Survey

A scalable cloud-based teleophthalmology architecture for AMD detection with the IoMT was presented by Das et al. [9] . Under the suggested architecture, patients wear an OphthoAI IoMT headset head-mounted camera, and relays Personalized illness severity with a private cloud drive assessment and projected development prediction. The images will then be processed by a AMD disease severity detection and quantification convolutional neural network proposed, which contains 152 layers.After training the system on over 130,000 fundus images from the NIH's Age-Related Eye Disease Study over a 12-year period, it achieved 94.97 ± 0.5% sensitivity and 98.32 ± 0.1% specificity for assessing AMD severity .The likelihood of forecasting pCR with just the nodal diameters of the first three treatments was examined by Feng et al. [10].The real nodal sizes of the first three treatments and the expected nodal sizes of the next three treatments based on the first three treatments' nodal sizes were used to screen for the optimal feature combinations for each breast cancer subtype. The statistic was used to evaluate the prediction. After just three treatments, a patient with TN may have an estimated pCR of Avc = 0.8696. In this study, Avc = 0.7594 was at least attained for each of the four subtypes of breast cancer. A nuclei-aware network for IDC grading in pathological pictures was proposed by Yan et al. [11] to obtain the fine-grained and nuclei-correlated feature illustrations for IDC grading, and the whole network achieves a role equivalent to the attention mechanism during end-to-end learning.

. It should be noted that our approach can highlight certain regions, offering a means of modeling medical information inside the network architecture. Unlike the general attention mechanism, which is incapable of manipulating the focus region, this one is. The literature on AI's application for three cancer diagnoses and projections—breast, lung, and oral cancer—is reviewed and summarized by Sadeeq et al. [12]. Various experiments are examined for the different kinds of early cancer detection methods. In order to improve cancer diagnosis and prognosis and promote overall health, this research provides a fresh perspective on AI technology. Chen et al. [13] the goal of applying machine learning (ML) models to build a predictive model for recurrence of breast cancer, focusing on a dataset sourced from patients in Taiwan. The dataset comprises clinical and demographic features, tumor characteristics, treatment history, and follow-up information. The proposed predictive model utilizes a combination of supervised learning algorithms, including but not limited to SVM, RF, and GB. Feature selection techniques are employed to recognize the utmost influential variables in recurrence prediction. Additionally, the model undergoes rigorous cross-validation to ensure robust performance and generalizability. Furthermore, the study investigates the impact of demographic and regional factors specific to Taiwan on breast cancer recurrence, acknowledging the potential influence of genetic variations and environmental factors. Incorporating these elements into the predictive model may lead to more accurate and personalized risk assessments for Taiwanese breast cancer patients. Assessment of models performance using Confusion matrix and area under the receiver operating characteristics curve (AUC- ROC). Comparative evaluations are carried out to evaluate the superiority of the proposed machine learning model over traditional prognostic methods. Soni et al. [14] proposes a Lightweight Authentication and Key Agreement Protocol designed specifically for IoT-based WBANs to address the unique challenges posed by resource-constrained wearable devices. The proposed protocol focuses on minimizing computational and communication overhead, ensuring efficient and secure authentication between wearable devices and the healthcare infrastructure. Leveraging lightweight cryptographic primitives and optimized algorithms, the protocol aims to strike a balance between security and resource efficiency. It introduces a novel key agreement mechanism tailored for the dynamic and energy-sensitive nature of WBANs, fostering secure communication while conserving precious device resources. Roseline Ogundokun et al. [15] a new method to diagnose breast cancer trained neural networks with hyperparameter optimization bit neural networks with hyper parameter optimization bit neural network with hierarchical optimization in Cancer breast presented in conjunction with IoT-based medical devices. The proposed system leverages IoT-enabled devices for real-time data acquisition, including mammographic images, patient history, and clinical parameters. A comprehensive dataset is curated to train and validate hyper parameter-optimized neural networks, enhancing the model's ability to discern subtle patterns indicative of breast cancer. The hyperparameter optimization process is employed to fine-tune the neural network architecture, ensuring optimal performance and generalizability. The neural network model is designed to provide interpretable and explainable results, contributing to the transparency of the diagnostic process. The system's performance is rigorously evaluated using a diverse dataset, demonstrating its efficacy in terms of sensitivity, specificity, and overall accuracy. Moreover, the proposed solution is compared with traditional diagnostic methods to highlight its superiority in terms of speed and reliability. Dourado et al. [16] proposed a novel open IoHT-oriented deep learning architecture for real-time online medical image recognition. The framework leverages the power of interconnected medical devices and the availability of large-scale medical image datasets to enhance the accuracy and efficiency of medical image recognition tasks. The proposed framework integrates state-of-the-art deep learning algorithms with IoHT infrastructure, facilitating real-time collaboration between medical devices and cloud-based processing units. The key components of the framework include a distributed network of medical imaging devices, a centralized cloud-based deep learning model, and a secure communication protocol ensuring privacy and data integrity. Sara Alghunaim et al. [17] explores the scalability of machine learning algorithms in handling large-scale datasets for breast cancer prediction, leveraging the vast amount of diverse and complex data available in the era of big data. It starts with a complete analysis of available breast cancer prediction methods based on machine learning, outlining their advantages and drawbacks. Then the discussion focus on the Achilles' heel for the large size and complexity of the breast cancer datasets, and the scale problem to gather useful knowledge is stressed.To address scalability issues, we propose and evaluate parallel and distributed computing approaches for training machine learning models on big data platforms. The utilization of cloud computing resources and distributed frameworks to enhance the efficiency of model training and prediction tasks. Furthermore, we assess the impact of feature reduction and selection methods on scalability, aiming to optimize the computational resources required for processing large-scale breast cancer datasets. Through extensive experiments on benchmark datasets and real-world clinical data, we quantify the scalability improvements achieved by our proposed methods. We present comparative results between classical machine learning methods and their scalable versions in terms of accuracy, precision, and recall and computation time. Can Hou et al. [18], aimed to construct a prediction model based on machine learning methods for predicting breast cancer in Chinese women. By leveraging a comprehensive dataset encompassing clinical, demographic, and genetic information, our goal is to enhance early detection capabilities and facilitate personalized healthcare interventions. The dataset comprises a large cohort of Chinese women, including both diagnosed breast cancer cases and a control group of healthy individuals. Key features include age, family history, reproductive factors, genetic markers, and other relevant clinical parameters. Through rigorous preprocessing and feature engineering, it optimizes the data quality and extract informative features essential for accurate prediction. Kaushal et al. [19] proposes a novel segmentation approach for the analysis of medical images related to breast cancer using the Firefly Optimization Algorithm (FOA). The primary goal is to enhance the accuracy and efficiency of image segmentation, which plays a crucial role in the detection and characterization of cancerous regions. The proposed technique leverages the unique characteristics of FOA, inspired by the social behavior of fireflies, to optimize the segmentation process. FOA is employed to find optimal threshold values that effectively separate different tissue types within breast cancer images, thereby improving the delineation of cancerous and non-cancerous regions. The algorithm's inherent ability to balance exploration and exploitation makes it well-suited for optimizing the segmentation parameters in medical images. To validate the effectiveness of the proposed approach, extensive experiments were conducted using a diverse dataset of breast cancer images. Comparative analyses with existing segmentation methods demonstrate the superior performance of the Firefly Optimization-Based Segmentation Art and tech of accuracy, sensitivity and specificity. Experimental results demonstrate that the proposed approach not only improves the accuracy of segmentation, but also reduces computation, therefore is promising for efficient medical image analysis. Maes et al. [20] provides a comprehensive overview of the pivotal role played by these technologies in the field of healthcare. The integration of medical image computing techniques, such as image segmentation, registration, and feature extraction, has significantly improved the analysis of medical images. These processes enable the extraction of valuable information from complex datasets, leading to more accurate and timely diagnoses .With the success of machine learning algorithms, especially deep learning algorithms, in learning complex patterns, several researchers in the NI community have applied deep learning and machine learning techniques to neuroimaging problems and representations from medical images, contributing to the automation of image interpretation and decision-making. Gottesman et al. [21] provides guidelines for the application of reinforcement learning in healthcare settings, highlighting key considerations and challenges. Address the unique challenges of applying reinforcement learning in healthcare, such as data privacy concerns, interpretability of models, and ethical considerations. Discuss the variability and uncertainty inherent in healthcare data, necessitating robust algorithms and exploration-exploitation strategies. Outline potential future directions for research and development in RL for healthcare. Highlight ongoing challenges, such as scalability, regulatory acceptance, and long-term model robustness.

3. Pre-trained Model for Cancer Cells detection

VGG19, it is a deep convolu- tional neural network architecture widely used in different computer visions tasks, including image classification. VGG19 is applicable for cancer cell detection, yet it is necessary to know that it would be subject to transfer learning. 9 is pre-trained on a large dataset (ImageNet). The pre-trained VGG19 model is also adopted to serve as feature extractor. The transfer learning used to eliminate the top (classification) layers of the VGG19 architecture and kept the convolutional layers. These layers can help in learning the most discriminant features of your cancer cell images.

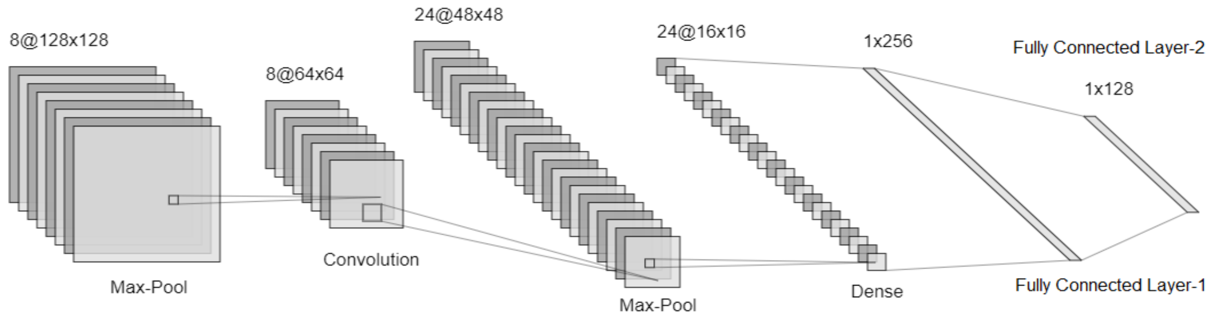

Figure 3: Architecture of VGG-19

4. Algorithm Steps

Step-1 Used Pre-Trained model with VGG-19

A deep, pre-trained convolutional neural network called VGG-19 was created utilizing 1.5 million ImageNet images.The network, which has 19 layers, is capable of classifying photos into 1000 object categories, including several animals, keyboards, mice, and pencils. As a result, the network has acquired rich feature representation from a range of pictures. For the purposes of this discussion, however, VGG16 contains 16 layers (13 convolution layers and 3 fully connected layers), while VGG19 has 19 levels (16 convolution layers, 3 fully connected layers, 5 MaxPool layers, and 1.

Input: A 224 x 224 picture is sent into the VGG19.

Layers of Convolution The smallest size to capture left/right, up/down, and center is 3×3 convolutional filters, which are used in all VGG Conv layers. Maximum down Maximum up Maximum left Maximum right Maximum left/right/up/down. After that, a ReLU activation is applied.

Fully-Connected Layers (FCL): The VGG19 consists of the three fully connected layers. In 3 of the layers the first 2 have 4096 and the third 1000 which is the no. of classes in the imagenet dataset..

Step-2 Pre-processing with image filtering approach.

Use Bilateral Filter to eliminate the Photon Noise of input image MRI. It's a nonlinear filter that maintains edges while smoothing out pictures. It is frequently employed in image processing applications, such as medical image analysis, where it is utilized to identify cancer-affected areas in images. Additionally, the following formula defines it:

$$\mathrm{Bilateral\ Filter}(\mathrm{I}, \sigma_d, \sigma_r) = \frac{1}{W_p} \sum_{q \epsilon \Omega} \mathrm{I}(q) \cdot G_d\left(\|p - q\|;\ \sigma_d\right) \cdot\ G_r(|\mathrm{I}(p) - \mathrm{I}(q)|;\ \sigma_r)$$

- I is the input image.
- p and q are pixel coordinates in the image.
- G_d is the spatial domain filter, which is typically a Gaussian filter and is determined by the spatial distance between pixels p and q.
- G_r is the range domain filter, which is also typically a Gaussian filter and is determined by the intensity difference between pixels $\mathrm{I}(p) - \mathrm{I}(q)$.
- σ_d is the standard deviation of the spatial domain filter, controlling the spatial smoothing.
- $\sigma_r$is the standard deviation of the range domain filter, controlling the range (intensity) smoothing.
- Ω is the spatial neighborhood around pixel.
- $W_p$is the normalization term, given by $\sum_{q \in \Omega} G_d(\|p - q\|;\ \sigma_d)\ \cdot\ G_r(|\mathrm{I}(p) - \mathrm{I}(q)|;\ \sigma_r)$

Step-3 Segmentation

Adaptive Thresholding for Cancer Cells or tumors Detection

A popular method in image processing for segmentation tasks—such as the identification of things like cancer cells in medical images—is adaptive thresholding. Using distinct thresholds for different areas of an image enables adaptive thresholding to handle variations in contrast and lighting more effectively. Adaptive thresholding is the method of determining a local threshold for every pixel by examining its surrounding properties. The two thresholding methods that are applied in this case to divide up the input photos are listed below.

Mean-based Adaptive Thresholding:

Local Mean: Compute the local mean $M(a, b)$ for each pixel (a, b) within a defined neighborhood.

$$M(a, b) = \frac{1}{W\ \times H} \sum_{i=x-\frac{W}{2}}^{x+\frac{W}{2}} \sum_{j=y-\frac{H}{2}}^{y+\frac{H}{2}} \mathrm{I}(a, b)$$

Where M(x, y) is the value of pixel at location (x, y) and W and H are the width and height respectively of the local area.

Thresholding: Assign a binary value to each pixel based on a comparison with the local mean.

$$\mathrm{T(a,b)} = \begin{cases} 1, & \mathrm{if I(x,y)} > M(a,b) \\ & \text{otherwise} \end{cases}$$

Gaussian-based Adaptive Thresholding:

Local Gaussian Mean: Compute the local mean $\mathrm{G(x,y)}$ using a Gaussian filter for each pixel$\mathrm{(x,y)}$.

$$\mathrm{G(x,y)} = \frac{1}{2\pi\sigma^2} \sum_{i=x-\frac{W}{2}}^{x+\frac{W}{2}} \sum_{j=y-\frac{H}{2}}^{y+\frac{H}{2}} \exp\left(-\frac{(i-x)^2 + (j-y)^2}{2\sigma^2}\right) \times \mathrm{I(a,b)}$$

Where σ is the standard deviation of the Gaussian filter.

5. Novel Framework Combined with IoT

The proposed model is combined with RNN and IoT. RNN is a type of artificial neural network that has shown promise in various applications, including cancer cell detection RNNs are especially and sequential-input tasks. Which makes them an attractive approach for medical data analysis, time series data in medical imaging or patient data for example. In the application of cancer cell detection, the sequence data may be received from different sources, including, medical images, genetic data, and/or clinical records and RNNs enable to process and analyse the sequences and to find out whether cancer is present. Cells. Cancer is an important cause of death in the world, and early detection is important for prognosis. Detecting cancer cells in various tissues and organs is a complex task, often requiring the analysis of multiple data sources. RNNs can help in automating the process of cancer cell detection by analyzing the sequential data associated with the disease. Detection of cancer cells can involve a variety of data sources, including medical images (such as X-rays, CT scans, and MRIs), genetic sequencing data, and patient records. RNNs can process these data sources as sequences to capture patterns and abnormalities. The detection of cancer cells is challenging due to the variability in cancer types, stages, and the inherent noise in medical data. RNNs need to address these challenges by learning meaningful representations from the data and making predictions based on these representations. RNNs are well-suited for sequential data analysis because they can capture dependencies between data points over time. In the context of cancer cell detection, the architecture of the RNN may vary depending on the data source. For medical images, you can use convolutional recurrent networks, while for genetic data or patient records, a simple recurrent network might suffice. Data preprocessing is a critical step in RNN-based cancer cell detection. It includes the preparation of data through cleaning it - normalization, handling missing values, and feature extraction. For medical images, preprocessing might involve resizing, normalization, and augmentation. For genetic data, you might perform sequence alignment and feature extraction. Interpreting the decisions made by the RNN is essential in medical applications. Understanding which features or patterns the model is using to make predictions can help build trust in its results. Once a well-performing RNN model is developed, it can be integrated into clinical workflows for cancer cell detection. This may include live analysis of medical images, genetic data or patient records to give health professionals insights and aid in decision-making. Cancer cell detection is a rapidly evolving field, and ongoing efforts to enhance the accuracy and efficiency of the detection techniques. Keeping up with the latest developments in RNN-based cancer cell detection is crucial for ensuring the best outcomes for patients.

The binary cross-entropy loss used in training an RNN for binary classification:

$$L(y, \hat{y}) = -(y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y})) \quad (5)$$

- y is the ground truth label (0 for no cancer, 1 for cancer).
- $\hat{y}$ is the predicted probability that the sample has cancer.
- The loss function penalizes the model for predictions that are far from the actual labels.

6. The Steps of RNN Model:

Step 1: The parameters and hyper-parameters are initialized by considering the weights W_{hx}, W_{hh} biases b_h for hidden layer computations, as well as weights W_{hy} and biases b_y for the output layer.

Step 2: At each time step t, calculate the hidden state h_t using the input x_t and the previous hidden state h_{t-1}.

- Compute the output based on the hidden state.

$$y_t = \text{softmax}(W_{hy} h_t + b_y)$$

Here, tanh is the hyperbolic tangent activation function, and softmax is used for multi-class classification to convert the raw scores into probabilities.

Step 3: Compute the loss between the predicted output y_t and the target output $\hat{y}_t$.

Step 4: Back-propagate the gradients of the loss WRT the parameters. Optimize the weights and biases using optimization algorithm, eg : gradient descent and its variants Adam etc.

$$\frac{\partial \mathrm{Loss_t}}{\partial \mathrm{W_{hx}}}, \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{W_{hh}}}, \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{b_h}}, \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{W_{hy}}}, \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{b_b}}$$

$$\mathrm{W_{hx}} \leftarrow \mathrm{W_{hx}} - \alpha \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{W_{hx}}}$$

$$\mathrm{W_{hh}} \leftarrow \mathrm{W_{hh}} - \alpha \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{W_{hh}}}$$

$$\mathrm{b_h} \leftarrow \mathrm{b_h} - \alpha\alpha \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{b_h}}$$

$$\mathrm{W_{hy}} \leftarrow \mathrm{W_{hy}} - \alpha \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{b_{hy}}}$$

$$\mathrm{b_y} \leftarrow \mathrm{b_y} - \alpha \frac{\partial \mathrm{Loss_t}}{\partial \mathrm{b_y}}$$

Step 5: Repeat steps 2-4 for each time step in the sequence.

7. Dataset Description

The tumor images and health analysis data are collected from the IoT sensors and Images collected from DLSR camera. Total images are 1000 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 is checked using Accuracy, Precision, Recall, f1-score.. The training set consists of 500 images of various cancer cells in the human body and 500 images of testing set.

8. Performance Metrics

The performance of proposed approach compared with various models is analyzed by using the following parameters. These parameters measure the overall count of the positives and negatives that represents the effected and not affected by using the confusion matrix attributes.

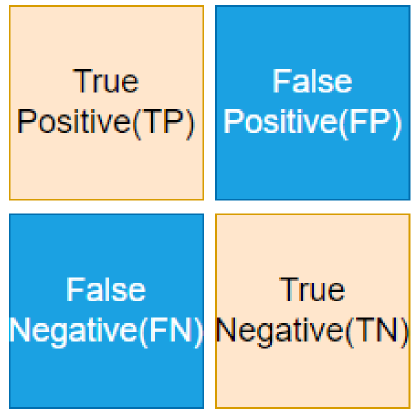

Figure 4: Attributes of Confusion Matrix

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

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

9. Experimental Results

The experiments focused on providing the analysis of given dataset images. These images are collected from various online sources such as Kaggle. The algorithm implementation is done by using Python programming language by using various libraries. The hardware set required for processing the input images is 8GB RAM and Intel Core i9-13900K processor. These requirements process the multiple input images to get the accurate images. This section mainly shows the performance in terms of training and testing loss with accuracy.

Training and Testing Loss:

The training loss cross-entropy quantifies how good of a job the model f is performing on the training data. It is calculated during the training stage at and is the difference between the model's predicted outputs and the true target values on the training set. The proposed pre-trained model VGG-19 used to minimize this loss in training phase. This is typically done using optimization algorithms like stochastic gradient descent (SGD) on given input images. The testing loss measures the performance of proposed VGG-19 model implemented on unknown data. Here, unknown data represents the input images with no labels. This is tested on a test-set that the model has never seen in training. This is called the validation set. The testing loss represents the quality of the capacity of the model to predict ideal that has been trained on the data. Finally, the testing loss is low with VGG-19 and this suggests that the model is performing well. Figure 5 shows the training and testing loss for the given input cancer images. The total epochs used in this context are 10. The training loss at 10^{th} Epoch is low with 0.031% and the testing loss at 10^{th} epoch is 0.028 which is lower than training loss.

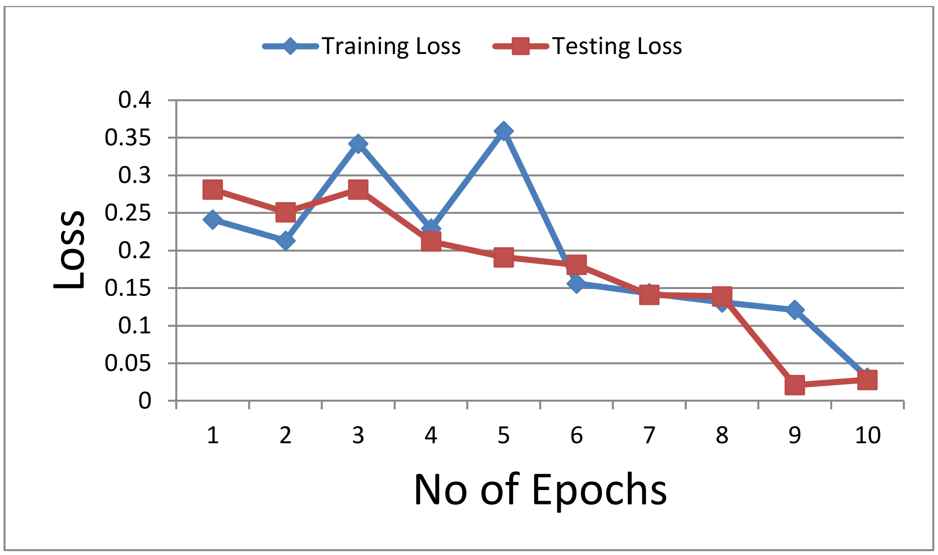

Figure 5: The training and testing loss of proposed VGG-19

Training and Testing Accuracy:

The training and testing accuracy for cancer cell detection which is crucial for assessing its performance. This is the efficient accuracy of the model on the training data. It shows how well the model did on the patterns it learned from the training data. The high accuracy on the trained data does not imply that the model will perform well with unknown data. This is the model performance on another set that was not seen by anything from the dataset was not trained. To test the performance of the model, we test the model prediction on other stimuli with the testing dataset. If the train accuracy is large and the test accuracy is low, you may be over fitting. Over fitting happens when the model is in fact learning from the training data and not overfitting to the training data itself. If both training and testing accuracy is low, then the model may indicate under fitting.

Under fitting is a phenomenon where the model is much too simple to model the complexities of the data.

Figure 6 explains the training and testing accuracy of proposed approach applied on cancer images. The training accuracy at 10th epoch is 0.131% and testing accuracy at 10th epoch is 0.234% which is high compare with training accuracy.

It provides an estimate of how well your model will perform on new data.

- High training accuracy (the model we've trained) ,Low testing accuracy.
- High testing accuracy (represents the model analyzes well to unknown data).

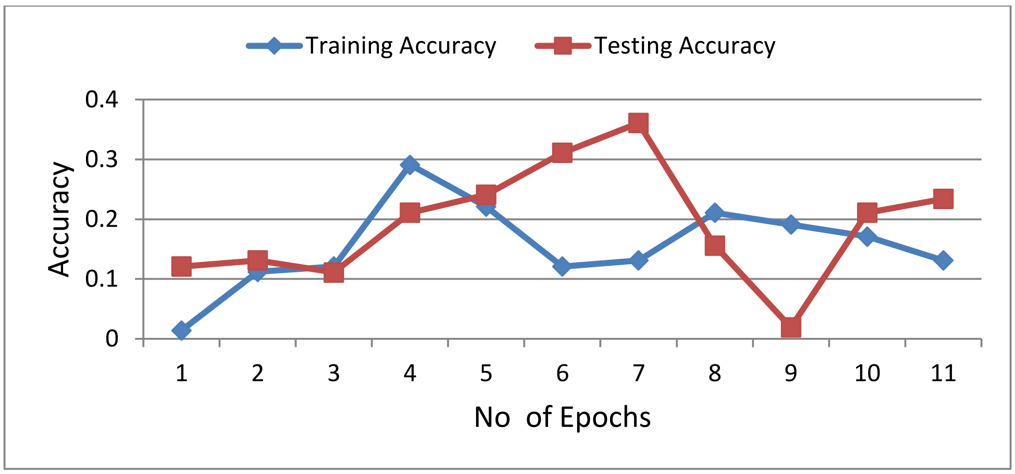

Figure 6:The training and testing loss of proposed VGG-19

Parameters	CNN	IoT with CNN	IoT with RNN
Accuracy (Acc)	94.34	99.12	99.45
Precision (P)	92.1	99.67	99.89
Recall (R)	93.34	98.34	99.45
F1-Score	95.1	99.56	99.87

Table 1: List of Algorithms that shows the performance in terms of following parameters.

Table 1 explains the overall performance of different deep learning algorithms in conjunction with the derived preprocessing and segmentation steps better accuracy compare with existing models.

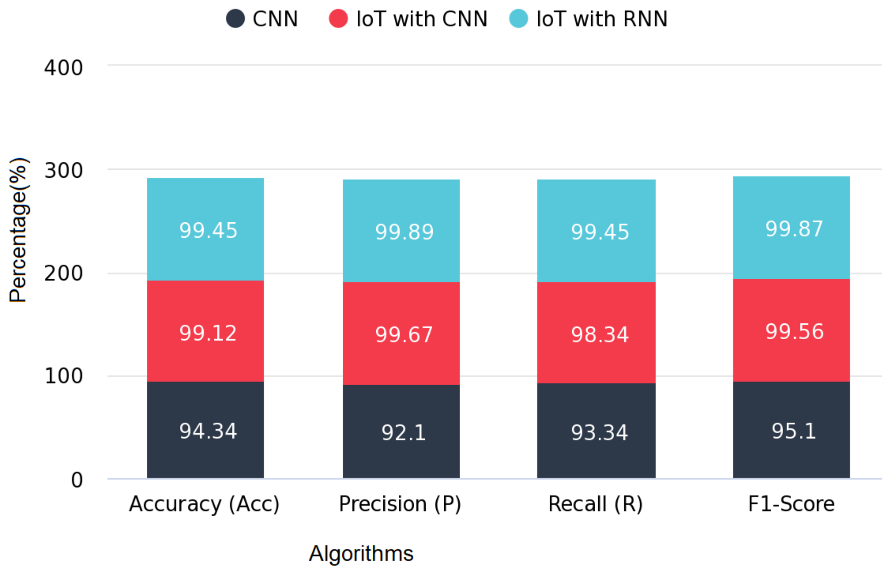

Figure 7: Competition between Deep Learning and IoT Models

10. Conclusion

Novel framework integrated with Internet of Things (IoT) for cancer cell detection system would be useful immense promise in revolutionizing the field of healthcare and diagnostics. The combination of IoT devices with innovative platforms for cancer cell identification greatly enhances potential for early cancer diagnosis. This may translate into higher treatment success and greater patient survival. It is easy to enable IoT devices to gather data continuously from different sources so we can monitor our health in real time. This allows for the immediate detection of any irregularities, such as the presence of cancer cells, and facilitates prompt intervention. The combination of novel frameworks and IoT technology minimizes the potential for human error, resulting in more accurate and reliable cancer cell detection. This, in turn, reduces the chances of misdiagnosis. IoT-empowered cancerous cell detection enables remote patient monitoring, consequently minimising the need of hospital visits. Patients would be able to have access to medical attention promptly after the onset of the symptoms and recommendations of treatments without leaving their homes. Machine learning principles can help to manage and derive value from the massive data generated from IoT devices. This can provide valuable insights into cancer cell detection trends, aid in the progression of better diagnostic and treatment strategies. By enabling early detection and remote monitoring, IoT-based cancer detection can decrease the cost of health care by caner not proceeding to advanced stages for which treatment is generally more expensive. Although such an approach provides many advantages, there are also concerns on data privacy, security and ethical aspects. Balancing the need for data collection with an individual's privacy will be a major hurdle. In the end, integrating a novel framework into IoT for the detection of cancer cells is a solid contribution in the fight against cancer. This novel technique has the capacity to bring about earlier detection, better accuracy, and financial efficiencies, while at the same time presenting significantly privacy and security challenges. Proper research, collaboration and ethical considerations with wearables have the potential to revolutionize how we diagnose and treat cancer, which will ultimately save lives and make healthcare more effective.

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