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ENHANCING SECURE AND SCALABLE CLOUD SOLUTIONS FOR MODERN HEALTH CARE USING DENSENET-121

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Keywords

Cloud Computing, Skin Cancer Classification, DenseNet-121, Wavelet Transform, Medical Image Processing, Healthcare Data Security

Abstract

Truly, cloud computing redefines and changes the healthcare server with the advances of using medical data and secure scalable storage. It is part of a deep learning process where it excels in improving diagnostic accuracy in other ways, especially through convolution neural networks, leading to advancements in diagnostic imaging. These current practices, however, are referred to as suffering noise problems, and they do not provide sufficient feature extraction. Moreover, there is not any current integration which offers real-time service delivery for health care through cloud computing. Therefore, such limitations make the systems developed with the use of current models generally unreliable and tough for scaling purposes related to cancer detection. This is building secure, scalable, and accurate skin cancer classification that leads to cloud services for real-time diagnosis, storage, and remote accessibility by health practitioners. Thus, it involves pre-processing-Median filtering and CLAHE; feature extraction-Wavelet Transform; classification-DenseNet-121; and cloud integration to store results. Hence, a well-performing model has well-scalability towards the efficiency of data. Hence, the developed system achieved 85.00% accuracy, 82.00% precision, 88.00% recall, and F1 score of 85.00%, making it a powerful diagnostic system as well known for its sensitivity values. Thus, this would be a cloud-integrated deep learning framework for better classification performance, providing easy access and security for health data.

1. INTRODUCTION

Traditionally seen as different services such as computation and storage, the current identity of cloud computing stands for highly labelled features and customization under flexible and scalable platforms that modern-day computing labels it with[1]. From the late 1800s to the mid-1990s, the idea that a 'cloud' could be 'connected grid of computers,' in which some designator for the internet could use from 1800 to mid-1990, was accepted as extremely valid[2]. Generally, while applying various terms, cloud computing has brought in a pay-as-you-go business model whereby cloud services can be customized for organizations unable to affordably operate such complex infrastructure [3]. It has now moved from allowing electronic access to health records to giving real-time access to relevant data for the patient or provider almost anytime and anywhere [4]. New operating paradigm in cloud gives improved service delivery, reduced operation cost, better security; improved data sharing among the afore-mentioned services [5]. All these imply a transition in service delivery for healthcare-from service-oriented and volume-driven to patient-centric to enhance quality and value and reduce the costs of care [6]. So, all these advantages should summarize to how much the healthcare domain has accepted cloud computing-in terms of what services it renders or benefits it offers to researchers in accessing greener, automated, economy-scalable solutions requiring little human intervention [7]. Real-time anomaly detection is essentially the enhancement of predictive modelling intelligence, which is concurrently personalized and automated for recommendations, greening, and the scaling of the economy [8]. Some of the most prominent advantages include lower capital costs incurred in business infrastructure, coupled with high scalability and resource optimization and improved agility-all of these becoming driving factors to a shift to cloud services [9]. As spelled, the paper insists on reputable and compliant providers, running the shared responsibility model in their Favor and thus exploiting the built-in security of-cloud platform [10]. Interminally, one would assume to categorize such on the basis simply of security concern attending to a lesser magnitude in regard to the service provided in the cloud environment by the provider [11]. Healthcare is surely under the hot scrutiny of the law as it goes through transformation or complete makeover [12]. EDI is then the technology that governed how vital information is exchanged in healthcare [13]. An in-depth implementation-oriented examination in the health sector has revealed the major barriers-the operational integration and the information security-that EDI would face in any implementation [14].

OBJECTIVES

Because skin cancer can be effectively identified with the help of dermatoscopy, an intelligent deep-learning-based skin cancer classification system can be designed considering security and scalability along with efficient technology for processing dermatoscopic images by advanced preprocessing techniques like Median Filtering and CLAHE for enhancement in feature quality and image clarity.

Implementing feature extractive methods through Wavelet Transform with classification using DenseNet-121 architecture is proposed with a better aim in high diagnostic performance with minimal overfitting and real-time true diagnosis of cancer at the point of detection.

Putting the classification system in sync with cloud storage services would give the diagnostic results secured and scalable remote access, helping healthcare practitioners with real-time availability of reliable medical data throughout the world.

2. LITERATURE SURVEY

Innovative trends affect the health care industry and the safety of their cloud space through the integration of IoT, AI, and advanced deep learning models in major sectors. The authors [15] proposed a remote healthcare monitoring system that incorporates either IoT connectivity spanning the communication between devices and machine learning models such as XGBoost and Bi-LSTM [16]. The proposed system achieved a 99.4% accuracy on heart disease prediction from the usual electronic clinical data (ECD) of patients coupled with their physical data measures, far better compared to other traditional approaches of diagnosis, emphasizing the value of continuous health monitoring for chronic diseases like hypertension [17].

This would ensure that security measures really do apply in any cloud environment [18]. Great ruckus had already been raised between ladies and gentlemen over Denial-of-Service Attack [19]. Create an RNN-LSTM analytical environment that would train on unique crescent patterns collected in network traffic [20]. The model will be trained by different sources that data would accumulate with high accuracy as well as lower false positives for better security against responses that evolve in the cloud from cyber warfare [21].

On the other hand, this mental health research has developed an architecture for sleep-state evaluation from EEG signals, using both the Internet of Things and Artificial Intelligence [22]. The Edge Device, Cloud Server and UI Application form the architecture that enhances the exact prediction of EEG activities and sleep stages [23].

Going into further details concerning healthcare, [24] made strides in the area of real-time patient data analyses embedded in Cloud-IoT systems [25]. The system under consideration had a whopping 90% accuracy and a precision rate of 94% in prediction using data mining and machine learning techniques such as SMOTE preprocessing, feature extraction (PCA), and classification based on optimized GANs [26]. The energy consumption and communication were optimized through the LEACH protocol within the system and in part provided it with improved efficiency and security using advanced encryption techniques [27].

The paper [28] refers to privacy-related issues associated with data sharing in healthcare. To enable hospitals to form a collective model learning from locality and while having sensitive patient information maintained, federated learning with the use of variational autoencoders is proposed [29]. The new sampling techniques of forming novel ways of aggregating groups have increased accuracy by 20.8% and reduced the cost of generalization to heterogeneous health data across disjointed institutions by 7% [30].

The generative AI family has become quite famous since the very beginning days of images [31]. For example, in a recently published paper, [32] discussed generative models-experimental GAN-for generating synthetic data, enhancing the quality of images, and assisting in abnormality detection on brain tumour MRI datasets [33]. Covers small dataset problem spaces and also opened discussions on ethics and the collaborative effort to ensure responsible AI in health care [34]. Then, with certain advancements in predictive modelling, an entirely new hybrid model combining broad learning and denoising autoencoders, called ABL, was introduced by[35]. The model was reported to be coping with some of the classical deep learning problems such as temporal instability in the gradients [36]. Thus, demonstrating incremental learning abilities, ABL quickly learns and attains a 98.50% accuracy on a number of medical datasets for its task about early prediction of diseases [37].

In the field of infectious diseases, [38] devised a TB diagnostic model that is lightweight and highly effective. It was built using Data Efficient Image Transformers and ResNet-16 for processing in the TBX11K dataset [39]. As a result, their system recorded an exceptionally high performance of 99.38%-accuracy and operated very fast in processing [40]. This suitability makes it ideal for practical tuberculosis detection and minimizes false alarms by differentiating it from other conditions affecting human lungs [41]. Enhancements regarding security for cloud computing [42]. who designed an optimized Intrusion Detection System based on Graph Neural Networks and Leader K-means clustering for better optimization [43]. This further fortified system by an optimized Grasshopper algorithm and secured by encryption and steganography proved to excel in accuracy of detection and processing speed on cloud computing with Java [44].

This is IoT and Deep learning in predictive healthcare: in the last chapter, [45] built an intelligent health system using Bi-LSTM for heart disease prediction [46]. Excelling in a fine line with an accuracy of 98.86 percent, the system can now transform the healthcare from reactive management into proactive interventions, capable of efficiently managing time series clinical records enabling the 'early intervention' of those at risk [47].

[48] These ground-breaking studies, clear antecedently, show how close AI, IoT, federated learning, and deep learning are to deploying advancements for deep applications in both healthcare and cybersecurity toward better world systems that are safer [49].

3. PROBLEM STATEMENT

Although strides are made in medical science, this will not stop skin cancer from being a mystery in early detection and identification as most of the former types of diagnosis were tedious, more or less subject to human errors, and therefore performed manually [50]. While this is the case, the skin cancer classification systems we currently possess cannot be viewed as highly competitive[51]. Hence the greatest need for an immediate and fast integrated cloud solution that can improve the quality of images, classify skin lesions with high accuracy, and securely store diagnostic results for access by healthcare professionals [52]. This paper therefore aims at answering all these challenges through a deep learning framework based on DenseNet-121 with subsequent advanced pre-processing and feature extraction approaches with the aim of achieving maximum possible diagnostic accuracy, real-time data accessibility, and secure safeguarding of health-related data[53].

4. PROPOSAL METHODOLOGY

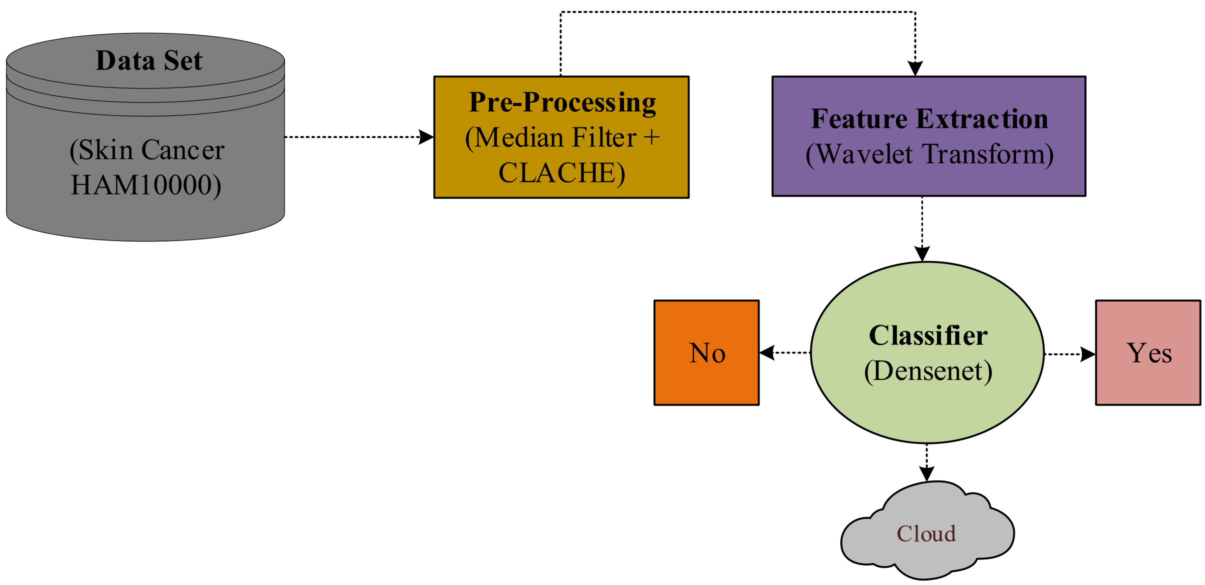

Figure 1: *Overall architecture of the proposed method*

The pipeline of secure and scalable cloud solutions in the health domain powered by convolutional neural networks takes as input images of skin lesions from the Skin Cancer HAM10000 dataset. Noise is eliminated using a Median Filter, contrast enhancement is done using CLAHE for the pre-processed images to enhance the important features in Figure 1. The Wavelet Transform is effective in capturing the spatial as well as frequency information and thus learning the features for distinguishing skin lesions. The features thus extracted are classified using Dense Net, which is a deep CNN architecture popular for its efficient propagation of features and limited overfitting. The classifier predicts the type of lesion as-"Yes" if it is positive for cancer and "No" if it is negative for cancer. In a positive detection scenario, the following would occur: transfer of the payload followed by a cloud location so that it may be scalable to reach healthcare practitioners anywhere in the world. As a result, it leads to increased diagnostic accuracy with real-time availability and safe handling of confidential healthcare data.

4.1 DATA COLLECTION

HAM10000, or "Human Against Machine with 10000 training images," is a dataset providing 10,015 dermatoscopic images of skin lesions which had been divided into seven diagnostic groups: melanoma, benign keratosis, basal cell carcinoma, etc. Each of the dermatoscopic images has accompanying metadata of high quality that firmly allow the dataset to be utilized for purposes of diagnosis. The images ensure that all samples are made to be consistent in terms of resolution.

4.2 PRE-PROCESSING

Pre-processing proceeds on two main operations aiming to increase the quality of dermatoscopic images in preparation for efficient feature extraction.

- ***Median Filtering:***

The median filter for noisy images eliminates salt and pepper noise while retaining significant edge information. For each pixel (i,j) in an image I, the pixel value is replaced with the median of its neighbouring pixels according to a specified window (e.g., 3x3 or 5x5). This is mathematically described as:

$$I'(i,j) = \text{median}\{I(m,n) \mid (m,n) \in \text{Neighborhood } (i,j)\} \quad (1)$$

Such a procedure guarantees the elimination of noise at small scales without running the risk of blurring the edges of the lesion, which remain vital in medical imaging.

- ***Contrast Limited Adaptive Histogram Equalization (CLAHE):***

CLAHE improves the local contrast in an image. The image is partitioned into small regions or tiles upon which histogram processing is done. In addition, a clip limit mitigates the excessive noise amplification due to this process. Mathematically, for a pixel intensity p:

$$p' = \text{CLAHE}(p) = \text{HistogramEqualize}\left(\text{clip}\left(H_p\right)\right) \quad (2)$$

were H_p is the histogram in the tile containing pixel p, After pre-processing, the dataset becomes.

$$D' = \{(x_i', y_i) \mid i = 1,2, \ldots, n\} \quad (3)$$

4.3 FEATURE EXTRACTION

Wavelet Transform is applied for feature extraction from pre-processed images. Basically, it creates a feature space where images get encoded with characteristics in both spatial and frequency domains so that very subtle patterns in skin lesions may be detected.

The Continuous Wavelet Transform (CWT) of a signal (or 2D image) $f(t)$ is defined as:

$$W(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-\tau}{s}\right) dt \quad (4)$$

were:

s is the scaling (frequency control), τ is the translation (position vs. time or space), ψ is the mother wavelet function, $*$ means the complex conjugate.

This transformation and communication can be made in three possible different perspective lines by two-dimensional applications of wavelet transforms. The effect of such feature combinations significantly improves the performance of classification, given that they contain the texture information pertaining to the skin lesions.

4.4 CLASSIFICATION USING DENSENET

After feature maps are obtained, they are fed to a DenseNet-based classifier. DenseNets are networks of densely connected convolutional layers that can be defined as a deep-learning architecture with a feed-forward manner of connecting all layers with all others in order to maximize the information and gradient flow through the network. Usually, in CNNs, a layer is connected to the next layer. But DenseNet does exactly the opposite: it concatenates the outputs of all the previous layers with the current one so that it allows feature reuse and dramatically reduces the number of parameters as such. This way, it also alleviates the problem of vanishing gradients. Thus, the drawn-out channels here extend further help towards a better training concerning feature propagation and eventually performance. The more complex is the imaging data-for example, medical imaging involving skin lesions, the greater is this. Thereby, DenseNet is one of the best-fit models in healthcare applications, which, by the way, are comparatively resource-hungry and are able at the same time to keep complex features for getting in precision. The inclusion of a DenseNet-based implementation inside the framework increases the robustness of the whole system against any classification error, thus promoting an explicit capturing and learning of latent patterns embedded in dermatoscopic images. The mathematical formula is,

$$x_l = H_l([x_0, x_1, x_2, \ldots, x_{l-1}]) \quad (5)$$

The operation Hl is a combination that entails Batch Normalization (BN), ReLU activation, and Convolution (Conv), while the inputs $[x_0, x_1, \ldots, x_{l-1}]$ constitute the concatenation of all preceding feature maps.

Finally, the sigmoid activates a function to determine the classification probability of a lesion being cancerous.

$$p = \sigma(z) = \frac{1}{1+e^{-z}} \quad (6)$$

If $p \geq 0.5$, the lesion is classified as "Yes" (cancerous); otherwise, it is "No" (non-cancerous).

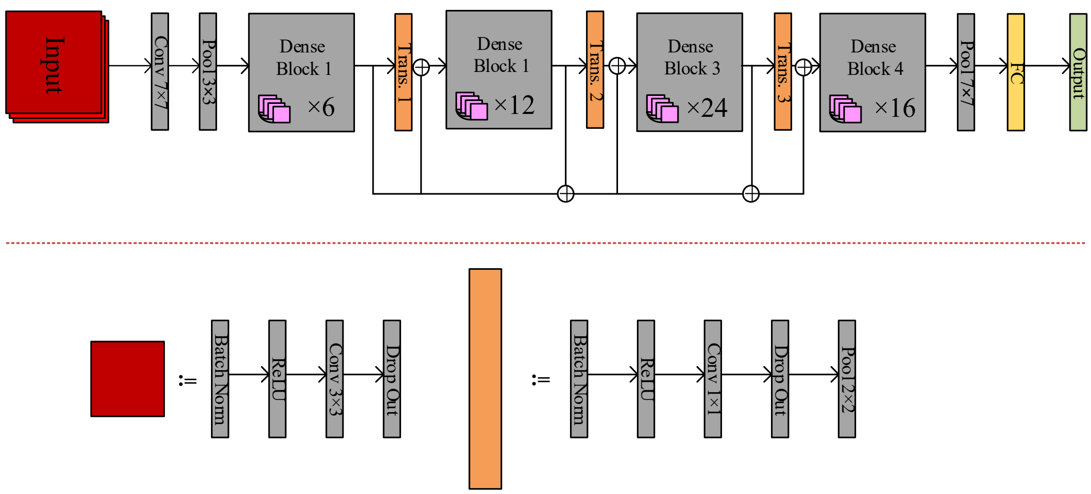

Figure 2: *Architecture of DenseNet*

The components of a DenseNet architecture in Figure 2 were diagrammed in such a way that every layer is feed-forward connected to every other layer. After this come the convolution and pooling layers of which there are four Dense Blocks having 6, 12, 24, and 16 layers respectively with each pair of succeeding dense blocks separated by a transition layer for size and dimensionality reduction. For each layer of the dense block, the input is a concatenation of all output coming from previous layers. This has improved gradient flow because it promotes feature reuse. Therefore, Global Average Pooling with a fully connected layer performs the classification task after the final dense block. For that, it is possible for an efficient computational performance, fewer parameters, and better performance of the model.

Step 1: Input Layer

The network starts with an input layer, where an image of dimensions H×W×C (Height × Width × Channels) is fed to the model. This input will further serve as the primary layer for feature extraction through the network.

Step 2: Initial Convolution and Pooling

Once upon a time, filters were applied to X to yield low-level features in its input convolution layer. The convolution operation is described mathematically by formulaic (1.1)

$$Y = X * W + b. \quad (7)$$

Here the *X* is the input image and *W* represent the filter weights while applying *b* as the bias. The convolution operation is mainly done to capture edges, colours, and some basic textures in it. Batch normalization follows after convolution to normalize the activations

$$\mathrm{BN}(x) = \gamma \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}} + \beta \quad (8)$$

Here, μ and $\sigma 2$ represent mean and variance of the batch, and these soft learnable parameters are γ and β. The output is activated through a ReLU, imparting non-linearity into the network; subsequently, the pooling layer diminishes spatial dimensions for the sake of controlling complexity and overfitting.

Step 3: Dense Block 1

The first stage of primary feature extraction by Layers is the Dense Block 1, which has six convolutional layers. Every one of these is densely connected with all previous layers, so that any given layer has as input the concatenation of the outputs of all previous layers.

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \quad (9)$$

were H l is a compound function of batch normalization, ReLU, and convolution, and [·] indicates the concatenation or the operation under which such dense connectivity would be regarded as encouraging feature reuse and decreasing vanishing gradients.

Step 4: Transition Layer 1

A transition layer follows Dense Block 1 and reduces the feature map size via 1×1 convolution and an average pooling operation. The degree of compression is determined using an adjustable factor θ. (typically $\theta = 0.5$):

$$\text{Output Channels} = \theta \times \text{Input Channels} \quad (10)$$

This keeps model sizes manageable in terms of training costs.

Step 5: Dense Block 2

The second Dense Block does not fall out of the parameters that are already set in the preceding block. But it differs from it, in that it has comparatively a greater number of densely connected layers being 12 in total. It facilitates better gradient flow and flow propagation in the feature space. It also improves the representation of the feature by ensuring that it is economical in the computations.

Step 6: Transition Layer 2

Substituting the dense Block 2. This ends up with yet another transition layer that now uses a 1x1 convolution followed by an average pooling to compress and down sample the features for deeper processing.

Step 7: Dense Block 3

The data are processed within Dense Block 3 that consists of 24 layers. Similar to the previous cases, each layer concatenates the feature maps of all previous layers within the block. This block is larger as more depth of features needs to be learned for better hierarchical feature representation.

Step 8: Transition Layer 3

At Transition Layer 3, which again diminishes spatial resolution and the number of channels, the intent is to have a compact input to the last dense block that is full of features.

Step 9: Dense Block 4

There are 16 layers in Dense Block 4 that are densely connected to each other. This last dense block succeeds in bringing out such high-level, abstract features needed for classification tasks. Similar to the former blocks, it employs concatenations of previous outputs for feature reuse.

Step 10: Classification Layer

There are 16 layers in Dense Block 4 that are densely connected to each other. This last dense block succeeds in bringing out such high-level, abstract features needed for classification tasks. Similar to the former blocks, it employs concatenations of previous outputs for feature reuse.

$$GAP(x) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j} \quad (11)$$

The result vector is passed through a single connection layer (dense) and is then given a softmax (multi-category) or sigmoid (two-options) activation.

$$\mathrm{Softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \qquad (12)$$

A high-efficient architecture with self-long-performance manners can enhance artistic space with respect to the knowledge increment achieved.

4.5 CLOUD INTEGRATION

Once classified, the results are handled as follows:

Once the decision is made in the classification, then that would hold for the destiny of the results. In this case, patient record (image, features, classification result) can be encrypted and safely uploaded to cloud storage for subsequent examination, remote diagnosis, and centralized maintenance of data. Otherwise, it cannot be uploaded to cloud storage in case of a no. This allows a highly scalable, secure real-time infrastructure for any kind of diagnosis-related information delivery to health care practitioners across the globe.

The final cloud upload operation can be symbolically represented as:

$$\mathrm{CloudUpload}\,(x_i', p_i) \text{ if } p_i \geq 0.5 \qquad (13)$$

Cloud integration assures a genuine assurance of data availability, encourages tele-care and healthcare outreach thus avoiding some drawbacks.

5. RESULT AND DISCUSSION

The experiments demonstrated the efficiency of the secure and scalable cloud integrated skin cancer classification system. The model went through an extensive training and testing process on the whole HAM10000 dataset and performance measured in terms of accuracy, precision, recall and F1 score. The two pre-processing techniques of Median Filtering and CLAHE were applied to images for enhancement while the Wavelet Transform was used for feature extraction enhancement and Deep feature learning was regularized by DenseNet-121. Title-Scalable cloud-based secure skin cancer classification: effectiveness tests on set-up experiments.

5.1 CONFUSION MATRIX

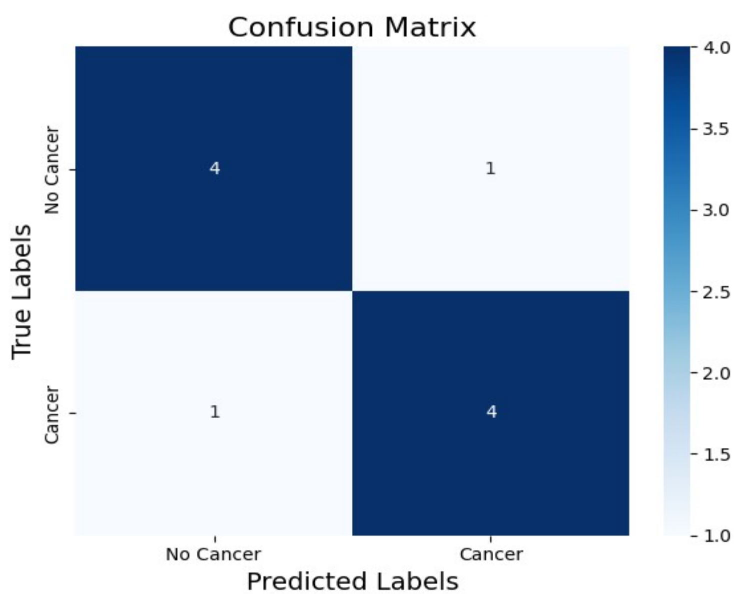

Figure 3: *Confusion Matrix Graph*

Confusion Matrix showing a general classification scheme: Cancer/No Cancer. The model classified 3 out of 4 No cancer instances as well as 4 out of n cancer instances. It reflected high discriminatory power. It falsely labelled one No Cancer sample as Cancer (false positive) and another Cancer sample as No Cancer (false negative). The classification errors are so small that it indicates the model being fairly accurate needing some touch up in Figure 3. The other feature showed by the matrix is a perfect balance between sensitivity and specificity in cancer detection.

Table 1 *Comparison Table of Performance Metrics*

Metric	Value
Accuracy	85.00%
Precision	82.00%
Recall	88.00%
F1 Score	85.00%

As these are the metrics for the classification model performance, an accuracy of 85% implies that the model has made correct predictions for 85% of total cases. Precision at 82% indicates that only 82% of those cases designated cancer were correctly diagnosed, which gives a minimum of false positives in Table 1. The value of recall is 88%; it tells us that the model was able to classify most of the cancer cases as positive; thus, it is sensitive. The F-Measure is at 85% indicating a balance of precision and recall; thus, the model has been able to maintain its performance overall. So, all these metrics assure the reliability and efficiency of the system to classify cancer and non-cancer images.

5.2 PERFORMANCE METRICS

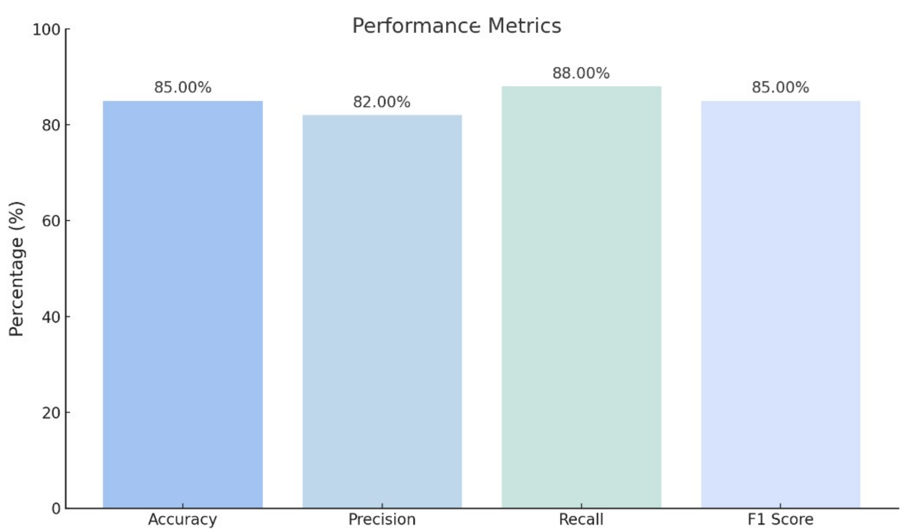

Figure 4: *Performance Metrics Graph*

The classifier performance in terms of accuracy, precision, recall, F1-score is shown graphically by a bar chart. The model has 85 percent accuracy which shows that majority of the instances got predicted correctly. As per Precision index, 82 percent of the positive identifications were correct. Recall throws another view of this model working really well with true positives with a really high score of 88 percent as shown in figure 4. An average F1 score calculated to be 85 percent is an excellent outcome and makes it strong and credible for any model performance. Brightly coloured use will enhance visual clarity and make the comparative assessment across parameters easy.

5.3 ROC CURVE

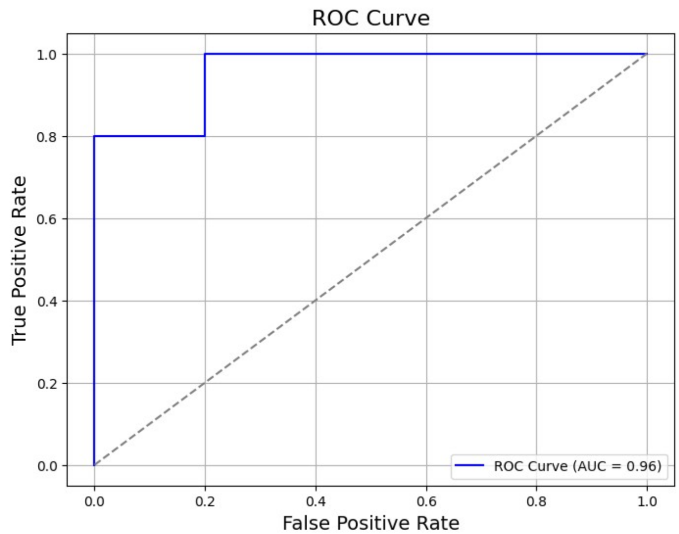

Figure 5: *ROC Curve Graph*

As has been mentioned above, the ROC (Receiver Operating Characteristic) curve assesses how well a classification model can discriminate between two classes. By showing the True Positive Rate and False Positive Rate in relation to various threshold values, the curve will form an effective shape to boast a superior model as in figure 5. The closer the curve is to the top left corner, the better the model performs. In this instance, AUC falls at 0.96- reflecting an excellent model with high sensitivity and specificity, as indicated by these values. The curve's steep upward slope and a considerable area under it would imply that the model has a strong ability to distinguish between positive and negative classes.

5.4 EFFICIENCY DISTRIBUTION

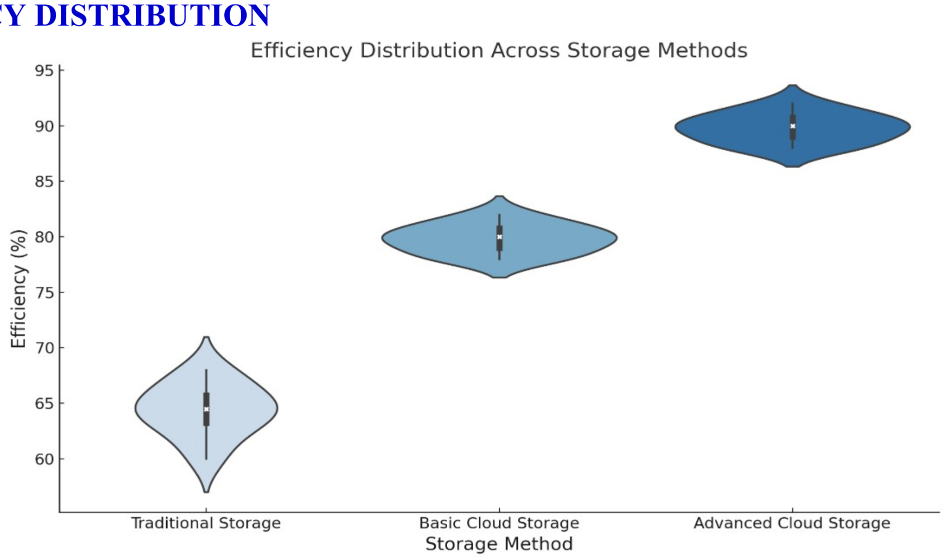

Figure 6: *Efficiency Distribution Graph*

This is a violin plot depicting the distribution of effectiveness across storage methods. The Traditional Storage shows lower and more widely dispersed effectiveness as it lies majorly in the range of 60% to 68%. Basic Cloud Storage shows a higher one with values crowding around 78% up to 82%. Advanced Cloud Storage shows the highest and the more consistent efficiency about 88% - 92%. The graph in figure 6 also indicates the superiority of cloud storage (especially advanced ones) over traditional stowage in efficiency.

6. CONCLUSION AND FUTURE ENHANCEMENT

This research paper discusses the implementation of a cloud-based model in classifying tissues pertaining to skin cancer with pre-processing feature extraction techniques based on DenseNet-121 and wavelet. The statistics shown by the metrics of performance achieved by this system ensure that its accuracy is 85.00% with precision being 82.00%, 88.00% recall, and an 85.00% F1 score. The above data clearly indicate that the model can differentiate lesions related to cancer from clinical manifestations not related to cancer, thus validly instigating higher sensitivity medical diagnosis. This is a good point for cloud-optimized systems, which are now promising secure and remote real-time access, the hallmark of contemporary health practice. In the future, there can be many exciting and very promising avenues for considering the enhancement of the working capacity model. Alternatively, one could load the model with a wide and rich dataset for generalizability across populations. Regarding areas of respective future consideration, hyperparameter tuning through optimization techniques could add a little heft in performance enhancement. Real-time networking methodologies are developed concerning computational efficiency and scalability, which will ultimately find adoption in live health-care settings. Knowledge modalities in AI could also play a role in clarifying the reasoning a trained model engages upon and instilling trust among clinician users. Finally, the establishment of the framework towards wider health care issues for diagnostic comprehensiveness will be the adaptation of the setup for other medical imaging applications.

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