Hindawi
Journal of Food Quality
Volume 2024, Article ID 9787530, 1 page
https://doi.org/10.1155/2024/9787530

Retraction

Retracted: Role of Artificial Intelligence and Deep Learning in Easier Skin Cancer Detection through Antioxidants Present in Food

Journal of Food Quality

Received 30 January 2024; Accepted 30 January 2024; Published 31 January 2024

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] S. R. C., J. G., S. N. et al., "Role of Artificial Intelligence and Deep Learning in Easier Skin Cancer Detection through Antioxidants Present in Food," *Journal of Food Quality*, vol. 2022, Article ID 5890666, 12 pages, 2022.

Hindawi
Journal of Food Quality
Volume 2022, Article ID 5890666, 12 pages
https://doi.org/10.1155/2022/5890666

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Research Article

Role of Artificial Intelligence and Deep Learning in Easier Skin Cancer Detection through Antioxidants Present in Food

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Received 13 March 2022; Revised 3 April 2022; Accepted 18 April 2022; Published 22 June 2022

Academic Editor: Rijwan Khan

Skin cancer is one of the most common types of cancer that has a high mortality rate. Majorly, two types of skin cancer are the most common, which are melanoma and nonmelanoma skin cancer. Each year, approximately 55% of individuals die due to skin cancer. Early detection of skin cancer enhances the survival rate of individuals. There are various antioxidants like vitamins C, E, and A, zinc, and selenium present in various foods that can be helpful in preventing skin cancer. “Deep Learning” (DL) is an effective method to detect cancerous lesions. The study’s purpose is to comprehend the vital function performed by DL methods in supporting healthcare professionals in easier skin cancer detection using big data networks. The present research analyzes the accuracy, sensitivity, and specificity of “Convolutional Neural Network” (CNN) for DL in the early detection of skin cancer. A statistical analysis has been done with IBM SPSS software to understand how the accuracy, sensitivity, and specificity of CNN change with the change in image number, augmentation number, epochs, and resolution of images. These factors have been considered independent variables, and accuracy, sensitivity, and specificity have been considered the dependent variables. After that, a linear regression analysis was carried out to obtain t and p values. The major scope of the study is to analyze the major role played by the DL models through the big data network in the medical industry. The researchers also found that when additional characteristics are present, image resolution does not have the potential to reduce image accuracy, specificity, or sensitivity. The scope of the study is more focused on using a DL-based big data network for supporting healthcare workers in detecting skin cancer at an early stage and the role of technology in supporting medical practitioners in rendering better treatment. Findings showed that the number of training images increases the accuracy, sensitivity, and specificity of CNN architecture when various and effective augmentation techniques are used. Image resolution did not show any significant relationship with accuracy. The number of epochs positively affected the accuracy, sensitivity, and specificity; however, more than 98% accuracy has been observed with epochs between 50 and 70.

1. Introduction

Skin cancer is the fifth most common cancer and has a high mortality rate. However, early detection of skin cancer increases the survival rate among patients. DL technology is one of the most efficient technologies for cancer detection. Different DL technologies are used by medical and healthcare professionals for easy and fast detection of cancerous cells. The current study investigates the accuracy, sensitivity, and applicability of DL’s “Convolutional Neural Network” (CNN) in the early diagnosis of skin cancer. According to the data of the sheer database of “National

Cancer Institute," there is a 90% survival chance of patients for 5 years on the condition that the detection has been done in the first stage [1]. The sheer database is also used by researchers and medical care professionals to analyze the 5-year survival rate of cancer patients, which usually decreases with disease progression. Different studies have proved that the DL algorithm can detect dermal cell damage through effective image classification technology and thus is an effective technology for cancer detection [2]. The first clinical diagnosis of skin cancer is made by observing visual symptoms in the patient's skin. These include dermal damage, skin lesions, abnormalities, secretions, and skin colour change. Different dermoscopic analyses were done to examine these dermal symptoms, such as histopathological tests and biopsy. These tests are accurate in observing the presence of malignant cells and malignant tumours in suspected patients.

The CNN is a DL algorithm that can effectively detect the presence of cancerous lesions [3]. The quality of advancements is related to total accuracy, specificity, and sensitivity. This suggests that the augmentation improves the picture quality of the patient. This happens because the augmentation improves picture accuracy by increasing resolution. CNN can effectively classify the images that are produced through patient dermoscopy. These images are classified to detect the type of cancer, such as whether it is melanomas or nonmelanomas. Melanoma is a type of skin cancer with a high fatality rate of 55 percent if not diagnosed early. The rising incidence of melanoma and nonmelanoma skin cancer has prompted medical and healthcare experts to express their concern.

The images of skin lesions are analyzed through image classifiers using DL to detect cellular damage. On the condition that abnormal tissue or cellular proliferation is detected, the report further precedes analysis through CNN. The major advantage of DL is its low-cost detection, high accuracy, and rapid testing. This image classifier effectively analyzes the accuracy rate and thus reduces the extra burden of "biopsy tests." Medical and healthcare professionals nowadays are relying on DL for the accurate detection of skin cancer. Another study has shown that the CNN of the DL algorithm has a higher accuracy level of 76% with a sensitivity of 95% [4]. This research has further shown that patients whose cancers are detected through CNN have an early and rapid detection compared to patients whose cancers were detected through biopsy. This early detection tends to enhance the survival chance of patients. The present research analyzes the accuracy level of DL in skin cancer detection. Statistical analysis has been done for this research with IBM SPSS software to measure the impact of the DL algorithm in the early detection of skin cancer. A linear regression analysis has been done in this research to see the accuracy level. Four independent variables are taken for this research: "input training image," "augmentation number," "epoch," and the resolution of the training images of CNN. This research focuses on demonstrating the impact of this cost-effective, sustainable, and rapid detecting algorithm in the effective analysis of skin cancer.

The goal of the study is to apprehend the critical role played by DL methods through big data networks in assisting the healthcare professionals in easier skin cancer detection and the implementation of big data networks; the researchers intend to set the scope of the research by using novel DL tools through big data networks to help healthcare care professionals in supporting better control in detecting skin cancer effectively. Machine learning technology is one of the most effective cancer detection technologies. Healthcare sector experts employ various DL technologies to identify cancerous cells quickly and easily. DL algorithms have been used in many studies to identify dermal cell damage using effective image categorization technology, making them an excellent method for cancer diagnosis. It can be stated that early detection often increases a patient's chances of survival. The current study analyzes the level of accuracy of LD in detecting skin cancer. Images of skin lesions were analyzed with a DL image classifier to detect cell lesions. Assuming abnormal tissue or cell proliferation is detected, the report is analyzed by CNN. The main advantages of DL are low-cost detection, high accuracy, and fast testing. This image classifier effectively analyzes the degree of accuracy and thus reduces the extra burden of "biopsy examination." Today, health and wellness professionals rely on DL to accurately detect skin cancer.

The current research has been divided into seven parts: the introduction and value of the current research are mentioned in the first part; the literature review is explained in Section 2; Section 3 sheds light on research and methodology; the discussion and findings are described in Section 5; the conclusion part has mentioned in Section 6; finally, the future scope of this research is mentioned in section 7.

2. Literature Review

The growing occurrence of melanoma and nonmelanoma skin cancer has become a statement of concern for medical and healthcare professionals. According to the statistical analysis of the World Health Organisation, the past few decades have seen the worst cases of skin cancer. Over 2 million people have been affected with nonmelanomas skin cancer and over 1.3 billion people have been affected with melanomas skin cancer [5]. This increasing rate also has caused a high mortality rate among patients due to inaccurate detection of skin cancer. Moreover, the detection time of skin cancer has a reciprocal relationship with the survival rate of patients. Thus, early detection has been proven to enhance the overall survival rate. DL is an effective AI technology that can detect the presence of malignant tumours by detecting skin lesions. Primarily, it detects the presence of abnormal cells through detailed image classification. Due to its high accuracy level, the abnormal tissues and cellular damage can be analyzed rapidly. According to the studies of Khamparia and other researchers, the CNN algorithm of DL is used to implement the "dense and max" pooling operations. This helps researchers effectively classify the nature of skin tumours and lesions [6]. Another advantage of this technique is it can detect the presence of

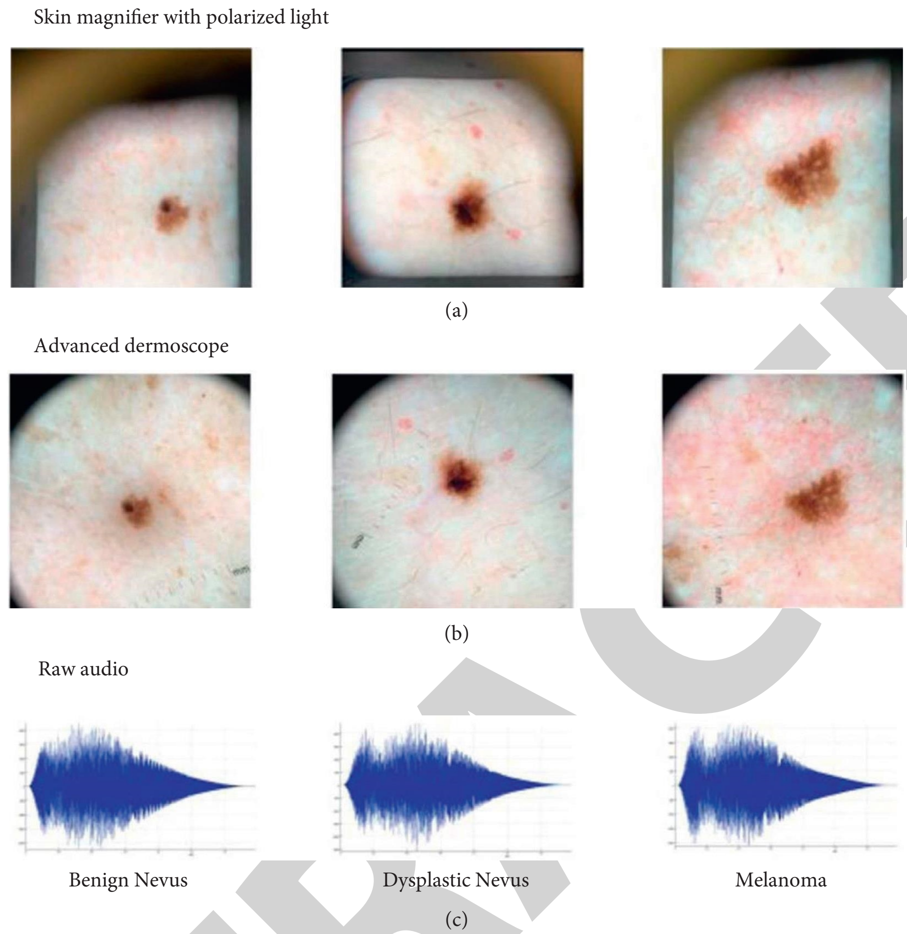

Figure 1: Detection of malignant lesions through skin magnifier using DL algorithm [10].

"malignant" and "nonmalignant" tumours and thus is efficient in detecting the disease progression rate.

According to the studies of Nahata and Singh, despite the high mortality rate of skin cancer, the survival rate of patients can be enhanced by 95%. This occurs on the condition that malignant tumours are detected early (in the first stage) [7]. DL methods require a huge dataset for training, which is a severe drawback. To illustrate, data covering numerous languages, demographics, and time spans are necessary for a speech recognition algorithm to get the intended outcomes.

DL primarily works via processing the images generated through a patient's biopsy in different layers. The image processing is done through different layers such as the "dense layer," "pooling layer," "convolutional layer," and "dropout layer." The "dense and max" pooling procedures are implemented using the DL CNN method. This enables researchers to distinguish the type of skin cancers and lesions more efficiently. These layers analyze patient images and segment them for a more accurate analysis of tumour type and illness increase. Patient images are processed in these layers and images are segmented for the effective analysis of tumour type and disease spread rate (metastasis).

As per the viewpoint of Abdar and other researchers, despite the high accuracy level of DL, there are significant limitations of these methods as the classifications sometimes can have "disastrous consequences" [8]. Researchers have proven that the "Naive Bayes" DL method is a significant AI algorithm that can effectively classify and segment medical images. The patient dataset is analyzed through the DL algorithm through a layered classification and segmentation system and a high accuracy rate of 90.6% can be achieved through this DL algorithm.

The studies of Barata and Marques have shown an interesting feature of DL through implementing this AI algorithm with traditional medical procedures. Their research has shown that DL algorithms can effectively analyze the "skin hierarchical patterns" [9]. In the traditional medication system, this hierarchical pattern is observed by doctors and healthcare professionals. This was done to describe the abnormalities in the skin and to demonstrate the abnormal patterns (such as lesion tissue inflammation, secretion, colour change, blood clot, and numbness) in the skin. DL technologies allow researchers to effectively follow this medication pattern and help researchers observe the structural changes that have occurred inside the epidermal layer. In this way, DL helps medical and healthcare professionals in analyzing oncogenic skin lesions in very less time.

Figure 1 depicts the studies of Fujisawa and other researchers who have shown that the use of skin magnifiers through "skin polarised light" can effectively detect the cancer progression rate. This progression rate is measured using raw audio and three different results are observed in "Benign Nevus,", "Dysplastic Nevus," and "Melanoma." Different results are also observed in the case of "advanced dermoscopy" and "skin polarised light." The results have shown that skin polarised lights are the most effective technology for analyzing the metastasis rate. There are several online websites for obtaining patient information, and a study may be undertaken such that numerous innovative techniques can be employed to correctly diagnose individuals and identify this condition before it becomes dead.

In [10], the DL algorithm is effective in demonstrating the lesion type progression rate and can effectively detect skin cancer. According to the studies of Khan and other researchers, an "Improved Moth Flame Optimization Model" with a DL algorithm can enhance the overall accuracy level by 98%. Their studies have proved that the DL algorithm is effective in skin cancer detection and through this highly accurate method, researchers and medical care professionals can improve the treatment quality in patients [11]. The fast and early detection enhances the survival rate of patients by 55%. The high survival rate reduces the mortality percentage in patients' and boosts their cognitive minds. In this way, the patients recover more rapidly and can live a healthy life. Therefore, it can be stated that the DL algorithm is the most accurate and effective method for the early detection of skin cancer.

Skin cancer has been witnessed as a serious problem that not only results in the death of human beings but also degrades the "quality of life." Skin cancer occurs in two types: one is benign and another is malignant. Therefore, doctors are demanding to accurately identify the type of cancer on the skin. Thus, AI approaches have been used for the accurate detection of skin cancer. DL is an advanced approach of AI, which makes it possible for effective discussion. David and David have used the DL algorithm for detecting melanoma on the skin [12]. Melanoma is a type of skin cancer that has a significant mortality rate of 55% when not detected early [13]. The authors have experimented with skin magnifiers and polarised light (SMP) to generate dermoscopy images. After that, the DL algorithms were trained on the images, and then specificity and sensitivity were measured. Apart from obtaining a pictorial dataset, they obtained an audio dataset (sonification) as well for a secondary DL. When SMP was used and DL algorithms were used, the results showed a 91.6% sensitivity (with F1-score) and 4.7% specificity. Therefore, when the significations results are obtained along with the dermoscopy image, the accuracy has improved.

It has been regarded that the implementation of innovative DL-based big data tools can enable analyzing the pattern and support forecasting the pattern effectively, as are variants of benign and malignant tumours. A faster CNN area (FRCNN) was then developed and the results were analyzed. The accuracy obtained is 86.1%. In addition, the authors compared the accuracy of dermatologists with the CNN algorithm. The level of expertise of the CNN algorithm correlates with the number of training images. Thus, it can be concluded that if the number of training images continues to improve, the probability of "overadaptation" increases rapidly. This reduces the accuracy level of the CNN algorithm (because the machine cannot detect true negative values). This in turn increases the likelihood of false-positive results.

Jinnai and colleagues have performed DL techniques using CNN to classify the images of melanoma. They have taken the images of pigmented skin from dermatologists to train the CNN algorithm. A total of 5845 images have been obtained by them to train their algorithm [14]. The pigmented skin images contain keratosis, sclerosis, melanoma, hematoma, and carcinoma. These are the variances of benign and malignant tumours. After that, faster region CNN (FRCNN) was trained and the results were analyzed. The accuracy obtained was 86.1%. Apart from this, the authors compared the accuracy of dermatologists with that of the CNN algorithm. Their comparison showed that dermatologists are 79% accurate, whereas FRCNN is 86.1% accurate. Dermatologists have predicted more than 13% of false-positive tests, whereas the DL algorithm provided only 5% of false-positive tests. However, why the study by David and David showed 91% accuracy has not been identified. The study did not mention which DL algorithm has been used. Contrarily, Rehman and colleagues stated that CNN is the most accurate algorithm in image classification due to its automated feature detection property. This automated technique is calculated by several scam detectives that examine each individual transaction and provide a binary response to each activity.

In [15], other algorithms can be accurate when autoencoders are placed; however, in these studies, no partial autoencoder has been used and CNN has been selected solely. Patients whose cancer is detected by CNN are detected in time and quickly compared to patients diagnosed with biopsy. This early detection often increases the patient's chances of survival. The current study analyzes the level of accuracy of LD in detecting skin cancer. In this study, we performed statistical analysis with IBM SPSS software to measure the effect of the DL algorithm on the early detection of skin cancer.

Concerning this, Kadampur and Riyaee performed DL with model-driven architecture using cloud computing. They observed 99% accuracy of the DL architecture. To perform the experiment, the authors used DLS or Deep Learning Studio (shown in Figure 2) with a model-driven architecture. Various types of skin cell images have been used in the DLS tools. After training using cloud computing, 99.76% accuracy was observed [17].

Kareem and coresearchers performed skin cancer detection tests using Deep-CNN or DCNN. They obtained desirable results. When GoogleNet CNN was used, the accuracy was 87.2%; when DenseNet CNN was used, the accuracy was 98%. Apart from this, the author compared CNN with "Support Vector Machine" as well [18]. "Support vector machine" (SVM) showed 90% accuracy, which is much lower than the accuracy of CNN. On the contrary, TR has observed 98.7% accuracy of SVM during skin cancer

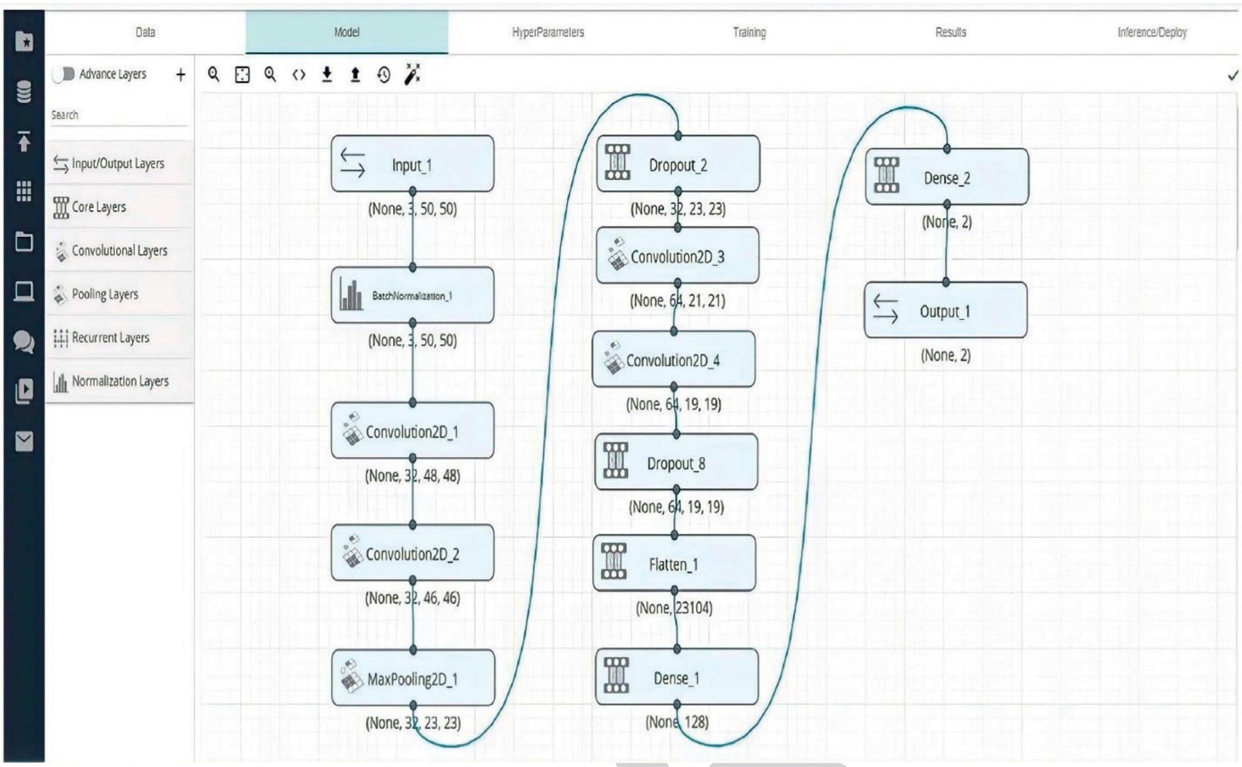

Figure 2: DLS model-driven architecture [16].

detection [19]. Therefore, confusion arises between these two studies. TR did not perform training and testing with SVM alone. The authors used Bendlet Transform with SVM to detect skin cancer and obtained more than 98% accuracy. It suggests that SVM alone cannot perform with 95–99% accuracy; however, when other encoders or bendlets are used, the accuracy of SVM increases.

Tan and coresearchers have carried out "Particle Swarm Optimization" (PSO) to improve the accuracy of DL architectures. After the experiments, they observed that the PSO of CNN and other architectures outperformed the conventional architectures. Apart from this, CNN has shown the highest accuracy among other algorithms. The IoT technology has been shown to be a powerful tool for connecting different sensor-based medical equipment and medical experts to bring high-quality medical services to flange areas [20].

The authors suggested that CNN and other algorithms can be optimized by swarm intelligence to improve accuracy. Figure 3 shows the proposed system architecture of Tan.

Tan and his coresearchers performed the same experiment one year before where it was observed that "Random Coefficient PSO" (RCPSO) has improved the accuracy of the DL algorithm in skin cancer detection [21]. The accuracy observed is 97.4% for K-nearest neighbour and 97.5% for SVM. It can be suggested that conventional DL or Machine Learning algorithms cannot function as accurately as CNN. Hence, new optimization techniques and autoencoders are required to increase the accuracy of SVM and other conventional algorithms. CNN performs better than the other algorithms because CNN consists of an autoencoder that detects the new features automatically, whereas other algorithms cannot; thus, an autoencoder or optimization is required [22].

3. Research Methodology

The present research has been done with primary quantitative data analysis through statistical analysis. The primary data have been collected by several dermatologists who are currently associated with different hospitals and healthcare sectors of the United Kingdom. The primary data contain different visual images of lesions collected from skin cancer patients. These data are analyzed through IBM SPSS statistical software to measure the image processing accuracy. A linear regression analysis has been done in this research to measure the impact of independent variables on the dependent variable. For the linear regression analysis, four independent and four dependent variables have been taken to determine the accuracy level of the CNN algorithm. The researchers also found that when additional characteristics are present, image resolution does not have the potential to reduce image accuracy, specificity, or sensitivity. As a result, it can be concluded that this research efficiently gives an understanding of CNN's involvement in the correct diagnosis of malignant tumours.

This research has been done to measure the impact of four dependent variables: input training image, augmentation number, epochs, and resolution of the CNN training images. The CNN method's performance is reduced as a result of this (because the machine cannot detect true

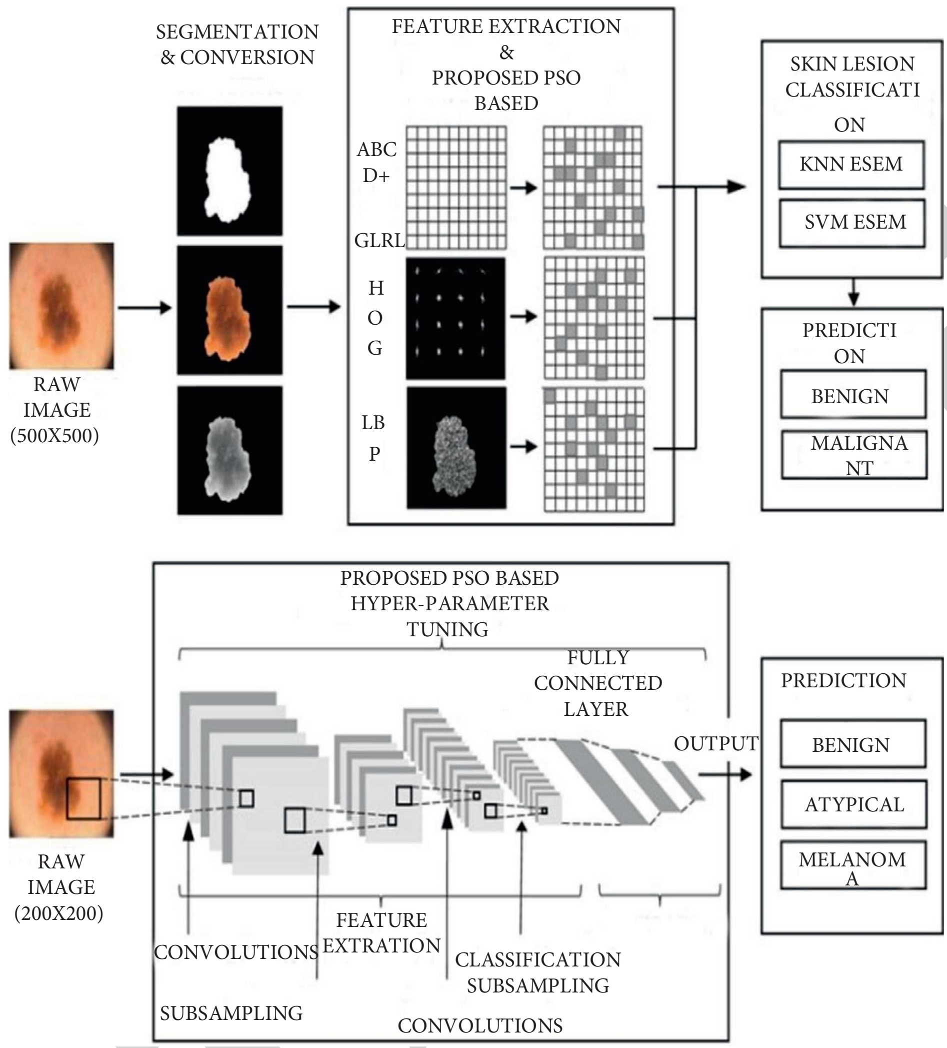

Figure 3: Proposed system architecture of Tan and coresearchers.

negative values). As a result, the chance of false-positive outcomes rises. When a large input dataset is used, CNN has a significant possibility of producing false-positive findings. This may be prevented by employing the right image classifier, design, and processor, all of which improve the overall segmentation technique.

The impact of these independent variables was measured on three dependent variables: specificity, sensitivity, and accuracy of the CNN algorithm. Over 250000 training images were taken for this research and linear regression analysis was done.

A statistical software has been taken, which is IBM SPSS version 26, and through this software, the regression analysis has been performed. This regression analysis is significant for this research as it effectively determines the relationship and statistical significance level of independent variables over dependent variables. A correlation analysis has been done at a 95% confidence level to measure the statistical significance and accuracy level. Secondary data analysis has been done to support the results of the primary data. The secondary data were collected from peer-reviewed articles and journals of the last five years (2018–2022) taken from Google Scholar. The research flowchart is shown in Figure 4.

3.1. Research Question

(1) How do the accuracy, specificity, and sensitivity of CNN change with the number of images, resolution, epochs, and augmentation?

(2) How do reducing false-positive tests in CNN increase the detection accuracy in the early detection of skin cancer patients?

4. Analysis and Interpretation

A linear regression analysis has been carried out to accomplish the research. Independent variables selected are as follows: input training image, augmentation number, epoch, and resolution of the CNN training images. In total, 250,000 images have been collected by dermatologists to train the CNN architecture. After that, regression analysis was done to understand how the independent variables affect the

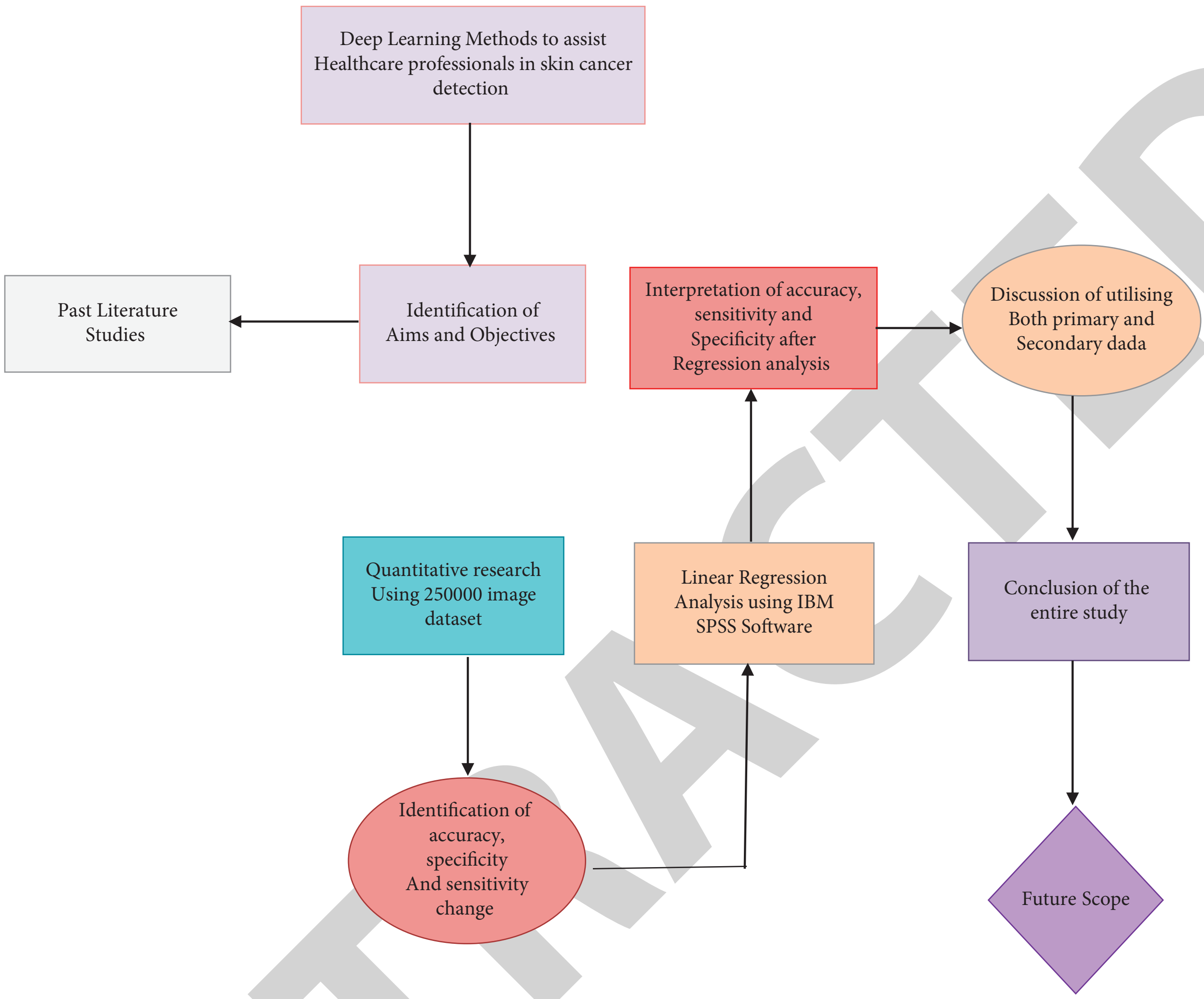

Figure 4: Research flowchart.

Table 1: Descriptive statistics showing frequencies of variables.

Statistics		Input training Images	Number of augmentations	Epochs	Resolution (x)	Sensitivity	Specificity	Accuracy of CNN
N	Valid	20	20	20	20	20	20	20
	Missing	9	9	9	9	9	9	9
Mean		107500.00	5.40	47.35	348.10	77.140	40.80	82.795
Std. Deviation		64226.163	2.683	29.635	175.317	14.0805	5.033	17.3127
Minimum		10000	1	1	90	46.0	32	53.4
Maximum		250000	9	95	720	92.3	48	99.9

sensitivity, specificity, and accuracy of CNN (dependent variables). The analysis output is shown below.

Table 1 shows the descriptive statistics where the minimum and maximum frequencies have been calculated in SPSS. A total of 250,000 training images have been taken and a minimum of 10,000 images have been taken to understand how the accuracy, specificity, and sensitivity change with increases in the number of images. A total of 9 augmentation techniques have been used: blurred image, mix-out, and mix-up, cropped, rotated in different angles, and blended. The highest resolution of skin images of 720×720 and the lowest resolution of 90×90.1–95 epochs have been considered. When these values have been considered, the highest sensitivity observed is 92.3%, the specificity is 48%, and the highest accuracy is 99.9%. However, this table does not signify how these independent variables are affecting the accuracy, specificity, and sensitivity. Therefore, regression analysis has been done to calculate the *t*-test and *p*-value.

The entire coefficient values have been calculated in SPSS; however, the upper limit, lower limit, and B values

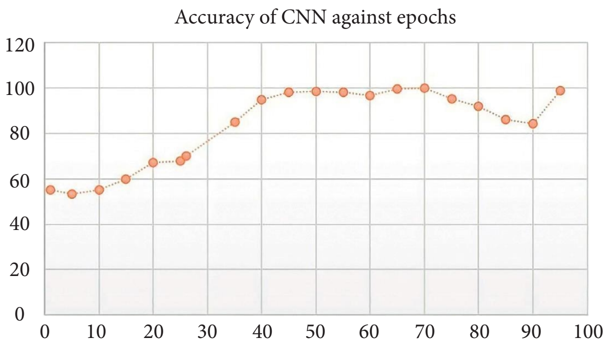

Figure 5: Accuracy of CNN with epochs shows maximum accuracy between 45 and 70 epochs.

Table 2: t and p values of accuracy, specificity, and sensitivity.

	Accuracy		Specificity		Sensitivity	
	T	Sig.	t	Sig.	t	Sig.
(Constant)	15.951	0.000	81.480	0.000	14.648	0.000
Input training Images	−0.013	0.990	−2.000	0.064	−0.427	0.676
Number of augmentations	8.227	0.000	4.549	0.000	1.877	0.080
Epochs	−0.089	0.930	5.861	0.000	1.323	0.206
Resolution (x)	−0.035	0.972	0.590	0.564	1.270	0.223

have been excluded; and only t and p values have been considered. The "number of input training images" has shown no statistical significance with accuracy ($p > 0.9$), specificity ($p > 0.06$), and sensitivity ($p > 0.6$). The specificity is weakly significant ($p > 0.06$), whereas the negative t value (-2.0) suggests that decreasing the number of training images increases the specificity. In every case, the number of training images is reciprocal to the t value of the dependent variables.

The number of image augmentations is statistically significant with the sensitivity, specificity, and accuracy of CNN in skin cancer detection. The p-value for accuracy and specificity is $p < 0.001$; however, sensitivity shows $p > 0.07$, indicating a weak significance. The p-value of these three dependent variables for epoch numbers is 0.9, 0.00, and 0.2, respectively, suggesting that only the specificity is statistically significant with the number of epochs. However, when the SPSS dataset was followed, it was observed that 45–75 epochs produced 98% accuracy (Figure 5). The current analysis has shown less accuracy in p-value identification due to the fewer number of experiments (20).

The images of different resolutions have been taken, and the accuracy, sensitivity, and specificity did not show any statistical significance ($p > 0.5$). In the case of specificity and sensitivity, when the resolution of images was increased, it showed higher sensitivity and specificity. The t value of accuracy is not promising here and thus neglected.

Table 2 shows the r-squared value, which can suggest that the average accuracy of the entire linear regression model for "accuracy" is 91.9%, with a standard error of 4.91%.

Table 3: Model summary output for accuracy.

Model summary for accuracy				
Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.968[a]	0.936	0.919	4.9136

a. Predictors: constant, resolution (x), number of augmentations, input training images, and epochs
b. Dependent variable: accuracy of CNN

Table 4: Model summary output for accuracy.

Model summary for specificity				
Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.994[a]	0.988	0.984	0.630

a. Predictors: constant, resolution (x), number of augmentations, input training images, and epochs
b. Dependent variable: specificity

Table 3 shows the average accuracy of the entire linear regression model for "specificity" is 98.4%, with a standard error of 0.63%.

Table 4 shows the average accuracy of the entire linear regression model for "sensitivity" is 84%, with a standard error of 5.63%.

Figures 6,6(a), 6(b), and 6(c) show the accuracy of CNN is not skewed in any of the two directions; however, the sensitivity is right-skewed and the specificity is left-skewed. The right- and left-side skewness suggest that the sensitivity and specificity do not change at a regular interval; instead, their values sometimes differ less and sometimes differ more (irregular manner). It has been observed that when the number of training images increased, the accuracy, sensitivity, and specificity increased; however, after the epochs crossed 75, the accuracy started to decrease.

5. Discussion and Findings

The current study employed primary quantitative data analysis using statistical analysis. The main data have been gathered by numerous dermatologists who are now affiliated with various institutions and hospitality industries in the United Kingdom. Table 1 shows that there is a weak statistical significance level between the p-value and the t value. The negative t value signifies that the specificity level of the CNN algorithm has a reciprocal relationship with the number of training images. Thus, it can be stated that on the condition that the number of training images enhances continuously, the probability of "overfitting" increases rapidly. This decreases the accuracy level of the CNN algorithm (as the machine is not capable of detecting the true negative values). This, on the other side, enhances the probability of false-positive results. From Table 5, it can be seen that the accuracy and specificity are negatively correlated with the input training images. This proves that as the total number of training images enhances, the overall specificity and accuracy of the CNN decreases. These data can be supported by the studies of Shakeel and other

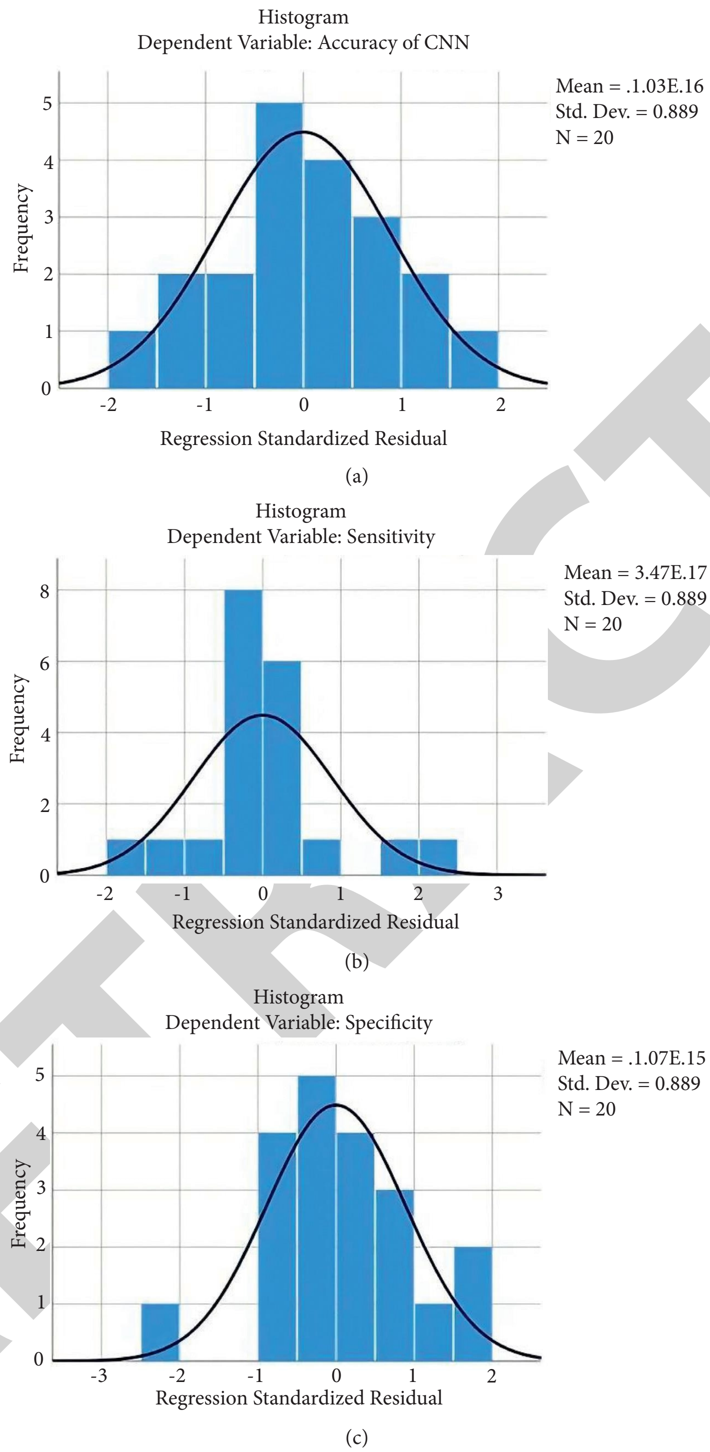

Figure 6: Histogram plot showing the skewed curve of accuracy (a), sensitivity (b), and specificity (c).

researchers. Their studies have shown that misclassification is one of the main reasons for accuracy and specificity reduction. They have shown that the "Improved Profuse Clustering Technique" can be used to reduce the rate of misclassification [22]. This enhances the overall image quality and processing quality of cancerous lesions. Figure 2 shows that the number of augmentations has a positive correlation with the overall accuracy, specificity, and sensitivity. This indicates that the augmentation enhances the patient's image quality. This occurs as the augmentation increases the resolution and thus enhances the image accuracy. According to the research of Toğaçar and other researchers, CNN can be used as a "consistent detection model" by improving its classification technique. The researchers have enhanced the number of augmentations to improve the image processing and classification of CNN. A

Table 5: Model summary output for accuracy.

Model summary for sensitivity				
Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.935[a]	0.873	0.840	5.6390
a. Predictors: constant, resolution (x), number of augmentations, input training images, and epochs				
b. Dependent variable: sensitivity				

(Source: created by the researcher).

significant 99.8% and 98.7% accuracy levels have been observed in their research through improving the augmentation [23].

In Table 1, it can be seen that the minimum resolution used for the present research is 90×90 and the maximum resolution that has been used is 720×720. The results have shown that after the change in resolution, no significant change has been observed in the overall accuracy, sensitivity, and specificity. This suggests that image resolution has no significant impact on the image processing accuracy of CNN when detailed features are visible. Other available studies showed that examination with different resolutions can have more than 91% accuracy (for example, 256×256 and 512×512) [24]. Thus, the current study is properly validated in terms of having no significant relationship in terms of accuracy, sensitivity, and specificity with image resolution.

From Table 3, the accuracy level and standard error level can be analyzed, which are 91.9% and 4.91%, respectively. These data show that the present dataset has an effective accuracy level and this can be improved using classifiers and processors. This statement can be supported by the studies of Ibrahim and other researchers. Their studies have shown that the use of "VGG19" architecture enhances the overall specificity, accuracy, and precision by 99.5%, 98.5%, and 98.47%, respectively [25].

Skin cancer is considered a serious problem that does not just lead to death. However, it harms the "Quality of Life.". There are two types of skin cancer: one is benign and the other is harmful. Therefore, doctors require you to identify the type of cancer appearing on your skin. Thus, the IM approach has taken its place in the exact detection of skin cancer. DL is an advanced artificial intelligence that enables effective conversation.

DL is an effective artificial intelligence technology that can detect the presence of malignancies by detecting skin lesions. It mainly detects the presence of abnormal cells with detailed image classification. The main benefits of CNN are its low cost, high accuracy, and quick testing. This picture classifier analyzes the accuracy rate, effectively reducing the additional load of "biopsy testing." DL is currently used by medical and healthcare experts for the reliable identification of skin cancer. Due to the high accuracy, abnormal tissue and cell damage can be analyzed quickly. DL's CNN algorithm is used to perform "frequent and maximum" concentration functions. This will help researchers effectively classify the nature of skin tumours and lesions.

From Table 4, it can be seen that the specificity of the present dataset is 98.4% and the standard error is 0.63%, which is a very nominal error. Again, from Table 5, the sensitivity can be seen at 84%, with an error of 5.63%. The data show that as the specificity increases, the overall sensitivity decreases and the machine loses its accuracy (as the data have been focused on testing linear regression on accuracy). These data have been supported by the studies of Ali and other researchers. In their studies, the researchers have shown the accuracy of the "training dataset" has a specificity and sensitivity of 99.1% and 99.2%, respectively. However, the overall specificity and sensitivity were 58.7% and 55.5% [26]. This shows that CNN has a high chance of providing false-positive results when a larger input dataset is being incorporated. This can be avoided using proper image classifiers, architecture, and processors as they enhance the overall segmentation process.

SPSS analysis showed that increasing epochs and augmentation of images increase the accuracy, sensitivity, and specificity of CNN architecture [27]. However, after the epoch passed 75, the accuracy started to degrade. This suggests that when the number of epochs exceeds a certain value, the data become overfitting and the accuracy decreases [28]. Chauhan and coresearchers have experimented with 50 epochs and the observed CNN accuracy was 76–80% [29]. Similar results have been obtained where the current study showed a CNN accuracy of more than 97% at 50 epochs. Another study by Vasan and others stated that 50 epochs produce the highest accuracy of CNN. Therefore, it is justified that 50–70 epochs are enough for obtaining more than 98% accuracy [30]. The current study showed that the mean sensitivity and specificity are 77.14% and 40.8%, respectively (Figure 7), suggesting that when CNN was trained with a large number of images, the false-negative results increased [31, 32]. However, the CNN detected true positive cancer cells with 77.14% sensitivity [33]. Hekler and coworkers also determined the sensitivity and specificity of the CNN algorithm, which showed 86.1% of sensitivity and 89% of specificity [34].

6. Conclusion

The current study has been carried out on 250,000 skin lesion images that contain cancerous and noncancerous lesion appearances. CNN has been fed with this large number of datasets along with negative control images that contain no skin lesions. It showed a maximum of 99.9% accuracy, 92.3% sensitivity, and 48% specificity. The number of epochs has affected the accuracy significantly, which suggests that CNN achieves >98% accuracy at 50–70 epochs. The specificity did not increase by over 48% probably due to the inefficient augmentation techniques and a large number of training datasets. Other available studies showed that the maximum numbers of skin lesion images taken were 30,000, whereas the current study fed CNN with more than 200,000 images, which resulted in false-positive or false-negative results due to overfitting. To eliminate the overfitting issue in the future, new DL algorithms will need to be improved. To achieve the best accuracy, certain DL algorithms still require autoencoder and optimization approaches. The major future scope of the study is to analyze the major role played by the

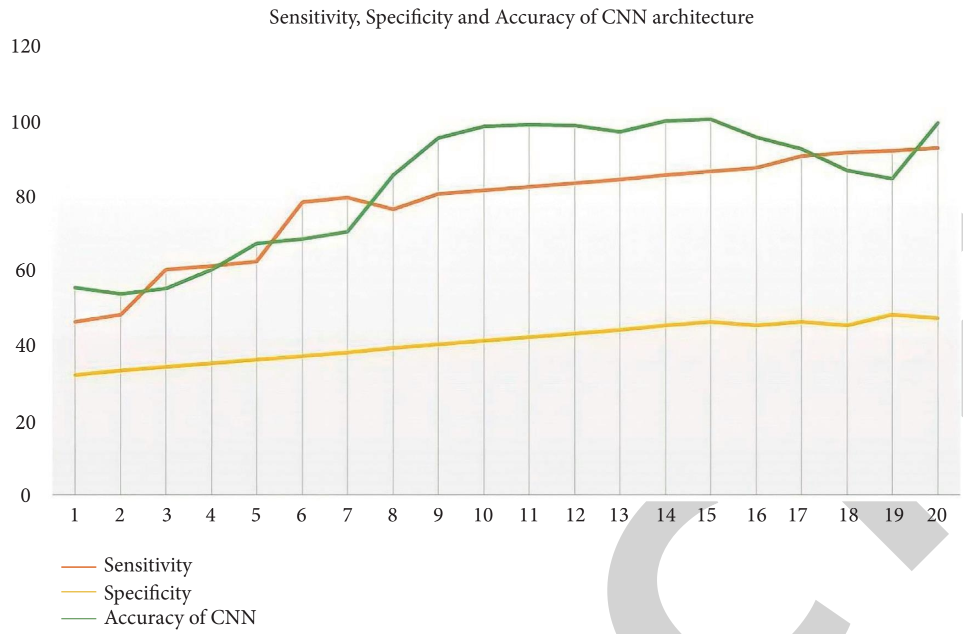

Figure 7: Graphical representation of accuracy, sensitivity, and specificity.

DL models through the big data network in the medical industry. The study also showed that the image resolution does not have the capability of reducing image accuracy, specificity, and sensitivity on the condition that other factors are present. Thus, it can be stated that this study effectively provides an idea about the role of CNN in the accurate detection of malignant lesions.

7. Future Scopes

Detection of medical images requires training of DL algorithms on a large number of training datasets that contain more than 50,000 images. Apart from this, different features, categories, and augmentations are considered for effective training, which can lead to overfitting of data. The overfitting is, therefore, responsible for developing less accurate results. Thus, the future DL algorithms need to be improved to eliminate the overfitting issue in the future. Some DL algorithms still require autoencoders and optimization techniques to perform with the highest accuracy. However, the CNN algorithm does not require any autoencoder, which suggests that the CNN algorithm with specific optimization techniques will increase the accuracy of image detection by 99.9% [35]

Data Availability

The data shall be made available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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