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Estimation of Skin Cancer with Integrated Extended Convolutional and Recurrent Neural Network Techniques on Image Dataset

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Abstract:
Skin cancer is the most common and possibly fatal type of cancer that necessitates early detection through the deep-learning method. Machine learning approaches such as random forest and Naive Bayes are used to identify skin cancer. Numerous studies comparing the efficacy of Artificial Intelligence (AI) based models for automated skin cancer classification to that of human experts have laid the groundwork for the effective deployment of AI-based tools into clinical pathological practice. The detection of skin cancer using Naive Bayesian display an accuracy of 86% and the random forest method exhibits an accuracy of 87%. To improve the accuracy, an automatic skin cancer detection using an Extended Convolutional Neural Network (ECNN) technique is proposed with 12 nested processing layers, which enhances skin cancer diagnostic and detection accuracy. The ECNN network and extended Recurrent Neural Network (ERNN) display an accuracy of 94.02% and 87.32%, respectively. These investigations assess the clinical relevance of three important aspects of the existing research on melanoma reader studies: test set characteristics (composition, and out-of-distribution dataset), experimental or clinical data (metadata), and clinical symbolism of the participants. These aspects are tested set characteristics (composition, and out-of-distribution dataset); experimental or clinical data (metadata), and clinical symbolism of the participants. The search included digital biomarkers, histology, whole slide imaging, deep learning, melanoma detection, and skin cancer categorization. The results suggest that ECNN and ERNN models are more resilient and dependable when compared to existing transfer learning models.

Keywords: Skin Cancer Dataset, Machine Learning, CNN, Deep Learning, RNN, ECNN, Health Data Analytics, ERNN, Artificial Intelligence.

INTRODUCTION

In common parlance, cancer refers to a wide spectrum of disorders that affect the human body. The sickness is essentially a weird cell development that attacks neighboring cells and spreads to organs of the body; this contact is referred to as metastasizing. Cancer is the world's second greatest cause of mortality, killing around 9.6 million people or one out of every six deaths (Bray et al., 2018). Skin cancer has recently become the most common and dangerous type of cancer detected in humans. It can take many distinct forms, counting melanoma, squamous cell carcinoma, and basal cell carcinoma, the latter of which is difficult to diagnose. Melanoma and non-melanoma skin malignancies have become more frequent in recent decades. Each year, there are between 2 and 3 million and 132,000 incidences of non-melanoma skin cancer worldwide. According to the Skin Cancer Foundation Statistics (SCFS), one in every five Americans is affected by skin cancer. Melanoma is the 19th most common malignancy in both men and women. In 2018, there were roughly 300,000 incidences of skin cancer. Non-melanoma skin cancer is the fifth most frequent type of cancer, affecting one million men and women globally (Nahata & Singh, 2020).

Because of their similarity, cancer detection and diagnosis are the most difficult for medical experts. Skin cancer cannot be noticed with the naked eye since it first starts as a little mole (Kadampur & Al Riyaee, 2020). Information Technology (IT) tools play an important role in disease diagnosis. The advancement of IT allows for advances in health care in disease diagnosis, management, and support. Improved decision support systems that are coupled with evidence-based medicines also help clinicians with the diagnostic process (Krive et al.,2015). Numerous researchers have employed IT to identify and diagnose skin cancer. Some of them used Machine Learning Techniques such as Naive Bayes, Random Forest, Agent Technology, and Neural Networks (Mahesh, 2020).

Deep Learning Technologies, such as Probabilistic Neural Networks (PNN), Artificial Neural Networks (ANN), and Convolution Neural Networks (CNN) on the other hand, has demonstrated the highest performance in skin cancer identification and diagnosis (Salvi, Acharya, Molinari, & Meiburger, 2021). Cancer is a serious threat to human life. It may risk human life on occasion. Various types of cancer may harm the human body and skin cancer is one of the deadliest. Smoking, drinking alcohol, allergies, becoming sick, acquiring viruses, being active, altering the environment, being exposed to ultraviolet (UV) light, and other factors contribute to it. The sun's UV rays can damage DNA within skin cells. Unusual bodily swellings can potentially cause skin cancer. According to Dorj, Lee, Choi, & Lee (2018), Actinic Keratoses, Basal Cell Carcinoma, Squamous Cell Carcinoma, and Melanoma are the four most common types of skin cancer. Pacheco and Krohling (2019), predict that skin cancer will account for one out of every three new cases of cancer. Skin cancer prevalence has steadily increased in the United States, Canada, and Australia over the last few decades.

Malignant Melanoma (MM) accounts for around 75% of all skin cancer deaths although accounting for only 4% of all skin malignancies. Early discovery and diagnosis are important for the survival of those who are afflicted [1].

On the other hand, because of the physical overlap between MM and atypical melanocytic nevi, early identification may be difficult. Despite the dermo copy enhances diagnostic accuracy over naked eye examination [2, 3], sensitivity levels above 80% are uncommon even for professionals. Aside from that, there is considerable diversity dependence on professional experience and training [4]. When an MM is suspected, a skin sample is conducted to allow for histological analysis. Even though the histological investigation is currently recognized as the gold standard for identifying skin cancer it is labor-intensive, time-consuming, and occasionally inconclusive. Individual pathologists' MM classifications varied by up to 25% among studies [5, 6].

LITERATURE SURVEY

Huge research has been conducted to discover and diagnose problems. The greatest ones pertinent to the present work were exhibited and discussed in detail. Earlier melanoma skin cancer hybrid approach for assessing worrisome lesions has been developed by Daghrir, Tlig, Bouchouicha, and Sayadi (2020). The suggested system is based on three prediction methods: CNN and two machine classifiers. The color, boundaries, and texture of the skin lesion are used to train the machine-learning classifier. Following that, these strategies are integrated to retrieve their presentations via a majority vote. The International Skin Imaging Collaboration (ISIC) dataset, which contains 640 images, was used to assess the functionality of the proposed system. The results show that when these three methodologies are combined, they attain the highest level of accuracy, which is 88.4%. Ulzii, as well as others, CNN, according to Dorj, Lee, Choi, and Lee (2018), is a smart and fast skin cancer classification system.

Furthermore, support vector machines (SVM) and error-correcting output coding were used to classify skin cancer (ECOC). Kaggle photos of skin malignancies in color RGB mode (red, green, blue) were collected and utilized to evaluate the performance. A specific set of photos contains noise from tools and other organs. The findings can be improved by trimming these photographs. The proposed algorithms were put to the test on 3753 photos of four different forms of skin cancer. The implementation findings show that the maximum average accuracy values are 95.1 percent. Melanoma is a type of skin cancer that results in the formation of malignant skin tumors. Skin cancer is detected using dermatological photos.

Machine learning based on a high-performance image detects skin cancer with high accuracy (Srividhya, Sujatha, Ponmagal, Durgadevi, Madheshwaran, et al., 2020). More features can, however, be retrieved to improve the model's accuracy, and the sensitivity is more varied. Hoshyar, Al-Jumaily, &Hoshyar (2014) developed a strategy for improving skin cancer diagnosis accuracy by using image processing techniques. They were unable; however, to describe precise cancer detection methodology. Another study's author offered an architecture-driven model for skin cancer diagnosis that used a Deep Learning (DL) algorithm. Because DL based on a model-driven architecture can be developed so quickly and the model can predict the outcome in the same amount of time. It improved its identification of skin cancer (Kadampur & Al Riyaee, 2020). However, real-time connection with medical pictures is essential for the technology to aid the medical industry.

According to the findings of Esteva et al. [8], a CNN-based deep-learning image classifier performed better than 21 clinical and dermoscopic dermatologists with board certification image classification. Because of this, the review was carried out by using the databases PubMed, Medline, and Science Direct for the English-language publications that were reviewed by peers and published between 2017 and 2021. (The search keywords were accessed for the very last time on February 17, 2021) Deep learning, melanoma detection, skin cancer classification, Whole slide imaging, histopathology, and digital biomarkers were produced by combining the following search terms. Table 1 gives a comprehensive overview of the search strategy.

The search results were reviewed by hand. According to literature provide a full summary of the PRISMA-compliant systematic search technique. Only publications that matched the requirements for inclusion were chosen. At first, the only study considered for inclusion was that which involved direct comparisons of AI classifiers with human professionals. This was because these methods better highlighted the potential value of AI-based classifiers in clinical pathological practice. Procedures that did not involve comparisons were left out of references [9-12]. In addition, only trials in which MM had a diagnosis were taken into consideration. Because Merkel cell carcinoma (MM) is the subtype of skin cancer that is linked to the highest mortality rate, it was considered research that entirely discounted the possibility of having Merkel cell carcinoma.[13]. In the end, the research that was primarily concerned with the classification of diagnostic criteria was only considered. Prognostic indicators such as therapeutic response and long-term survival were eliminated after painstaking analysis based on references [14-15]). Only peer-reviewed articles were used to retrieve the data. Two reviewers separately assessed the data's quality.

SYSTEM METHODOLOGY

Existing System

CNN and RNN are two separate algorithms used by deep learning researchers [21, 22]. Despite their extensive application and great outcomes, these tactics have the following limitations. The caveats of CNN and RNN techniques are shown in Table 1.

Proposed System

The methodical collection of relevant literature for this investigation was accomplished using the methods outlined below. To get things started, we gathered a list of research repositories, conferences, and journal papers related to computer science and digital humanities. Although many other places and fields, such as law, security and shadowing, and text dispensation, can fulfill these comprehensive supplies, we believed that our choices would be sufficient as a starting opinion for giving contemporary dialogues on the topic at hand.

We have compiled and organized all the releases for these websites, starting with the most recent and working backward in time by six years (inclusive of 2015-2020). 2015 was selected as the starting year for this project for two reasons. On the one hand, recent advancements in the utilization of known as deep learning or neural networks have significantly driven the current iteration of AI [19]. The ImageNet Large Scale Visual Recognition Challenge in 2012 was won by convolutional neural networks, which were 41% more accurate than their non-neural competitors (ILSVRC). Though neural network research has been going on for decades, it has only recently acquired general acceptance. Starting the emphasis in 2015 looked like the ideal moment to do so given the amount of time that would be required for these enhancements to affect a distant market such as documentation. In addition, because we wished to concentrate on recent disagreements and prospective perspectives, we investigated the possibility of employing modern AI [11-12]. Prior to this date, a cursory review of journals was sufficient to support our judgment. This research seeks to avoid the drawbacks of current CNN-RNN algorithms [30], as stated in Table 1, Table 2 describes how the suggested model enhanced prototype combines the CNN-RNN method to build a hybrid model with the following benefits [18].

Table 1: The Caveats of CNN and RNN Techniques

CNN	RNN
▪ Less precision and accuracy	▪ Small-data object detection is inefficient.
▪ The error rate is high.	▪ Good for predicting data labels, but not for segmentation
▪ High level of time complexity	▪ Less precision and accuracy
▪ Incapable of dealing with large amounts of data	▪ prone to errors

Table 2: Implications of the ECNN and ERNN approaches proposed

ECNN	ERNN
▪ High precision, low accuracy	▪ Easily detects small-data objects
▪ Relatively low error rate	▪ Excellent for data separation and forecasting.
▪ Reduced time complexity	▪ Precision and accuracy are quite high.
▪ Handles large amounts of data	▪ Less prone to errors

Input Data

The experimentation of this projected building was based on a dataset of 660 CT scan pictures from the Kaggle source https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000). Figure 1 depicts a portion of the input dataset that was segmented into two categories during the experimental stages: training cases and testing cases. These categories were determined by the results of the previous stage.

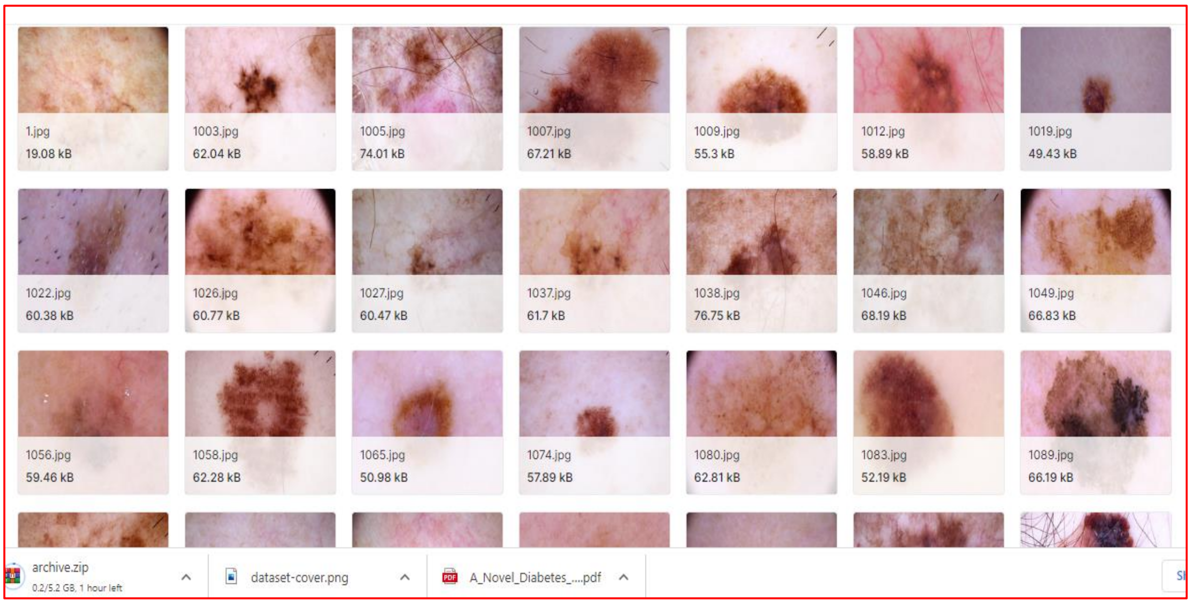

Fig. 1: Skin Cancer Virus Image Dataset in Kaggle Database

ECNN-ERNN Workflow Diagram

Figure 2 and Table 3 depict the suggested architecture for employing the ECNN algorithm to predict and detect skin cancer, which accepts a dataset from the Kaggle public repository and preprocesses it using many layers of the extended CNN approach.

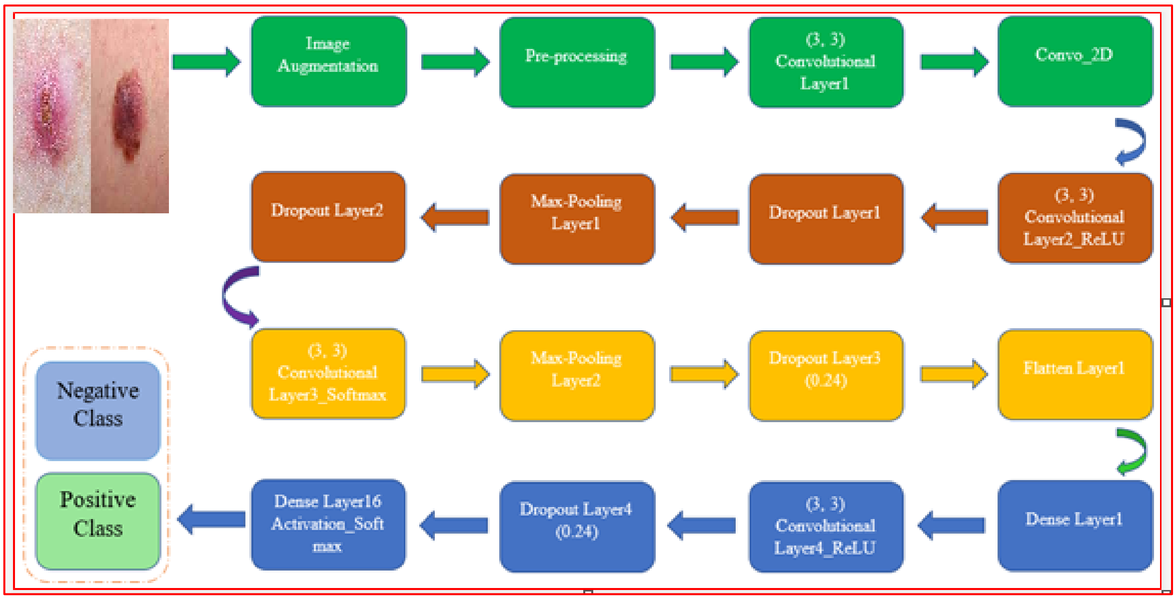

Fig.2: The suggested model's workflow diagram is based on ECNN

Table 3: The ECNN approach's algorithm steps

Step 1: Import required libraries
Step 2: Pre-processing of the dataset
Step 3: Combined CNN with Extended Neurons
Step 4: Perform 10-folded cross-validation with 2 classes
Step 5: Import Keras deep learning library with all supported libraries
Step 6: Reset all parameters of ECNN
Step 7: Enhance the ECNN part and regulation of the loss calculation function
Step 8: Enhancement of yield part of 10-folded with 2 classes
Step 9: Accumulate the ECNN parameters
Step 10: Adjusting the ECNN in the preparation of model
Step 11: Load the Skin Cancer disease infection image dataset
Step 12: Predicting the infection severity by classifying the dataset into 2 classes
Step 13: Outcome of the trained model and stop the model

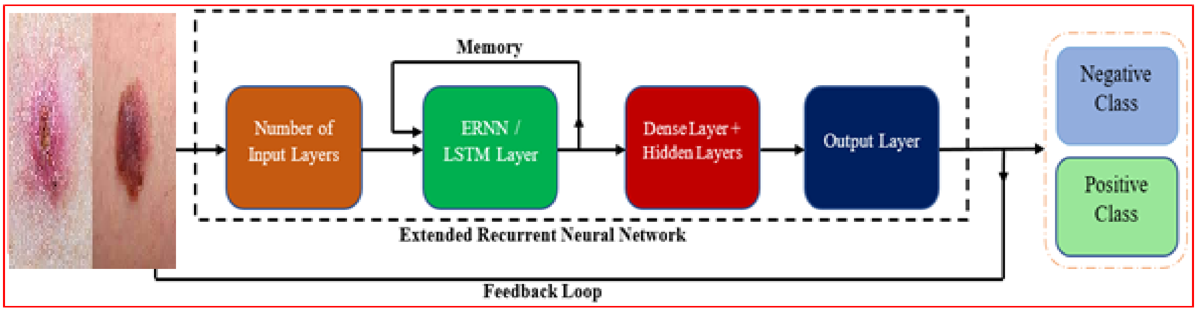

Fig.3: The suggested model's workflow diagram is based on ERNN.

Figure 3 depicts the suggested architecture for ERNN-based prediction and detection of skin cancer. Using ERNN/LTSM layers, dense layers, and hidden layers, the prototypical was qualified to predict the optimistic and undesirable classes in the provided dataset and then evaluated for precision, accuracy, and error ratio [26]. A wide range of DL models, including individual and assisted learning, have been proposed to solve several difficulties [27]. The nodes in the output layer are responsible for determining the probability of each label. Most of them are used for language learning, visual organization of images, and object recognition. In the relapse tier, activation activities are distributed across three fully interconnected layers containing 4095 hidden hubs. In this model, the projected thickness in millimeters is linked to the yield strength. The final yield layer is merely a single hub that has not been affected by the following factors:

Data Pool:
The challenging dataset comprised 660 rows and four columns, whereas the training dataset contained 660 images. The training dataset also contained 660 rows. The training database has 660 CT-scan photos spread throughout its four different columns.

ECNN-Layer:
A necessary component for the formation of neural networks. This is the most common and straightforward application of information levels [33].

ERNN-Layer:
It is a layer of recurrent neural systems in the deep learning approach. In this exploration article, this layer was reached out to address and demonstrate sequential and time-autonomous concerns, as well as well-being information forecast.

Pooling Layer:
Following the convolutional layer, another layer known as the pooling layer is added. Specifically, after applying a non-linearity, such as ReLU, with respect to the constituent maps produced by a convolutional layer; a model's layers, for instance, could look like this: It is necessary to enter image data [34–37].

ReLU-Layer:
If the performance is positive, it provides information both directly and indirectly. The evaporation gradient problem is solved by the updated direct-play action, letting the prototypical study earlier achieve improved [38]. The layer that contains all connections: A fully connected layer of brain material is one in which the influence of each layer is linked to each decision-making component in the layer below. The final few levels of most common AI models are fully linked layers that gather data from preceding layers to determine the production.

Output:
An optimistic, deleterious, or pneumonia accrue.

EXPERIMENTAL RESULTS

The fundamental motivation for the design and implementation of this framework is to facilitate the examination of picture data that conforms to preconceived notions of what should be there. Accordingly, structural constructs are means or strengths that demonstrate the structure, components, interfaces, modules, and data needed to implement the design principles. There is some sharing and cooperation between information gathering and the analysis of framework methodologies [15] and framework structures. The projected profitability of the application serves as the foundation for evaluating capabilities and implementations. The salient qualities have considerably aided systems research. /A dominant structure can be built using the patient's relevant fundamental qualities. Finally, it fits our requirements. It also intends to establish a strong bond with the system's current users by utilizing unique needs.

ECNN Algorithm

The suggested and required enlargement of CNN to an all-encompassing ECNN(s) is thought to improve accuracy, execution, and time complexity. Tables 3 and 4 show the steps the suggested model followed to attain high accuracy and a low error rate.

Table 4: The ERNN approach's algorithm steps

Step 1: Import required libraries
Step 2: Pre-processing of the dataset
Step 3: Combined RNN with Extended Neurons
Step 4: Perform 10-folded cross-validation with 2 classes
Step 5: Import Keras deep learning library with all supported libraries
Step 6: Reset all parameters of ERNN
Step 7: Enhance the ERNN part and ablation of loss calculation function
Step 8: Enhancement of yield part of 10-folded with 2 classes
Step 9: Accumulate the ERNN parameters
Step 10: Adjusting the ERNN in the preparation of model
Step 11: Load the Skin Cancer disease infection image dataset
Step 12: Predicting the infection severity throbyssifying the dataset into 2 classes
Step 13: Outcome of the trained model and stop the model

ERNN Algorithm

The Skin Cancer dataset was submitted to ERNN following the processes outlined below.
As a result, the computations yield more precise answers and take less time to complete, stipulating the image's data in early anticipation.

DISCUSSION OF RESULTS

The outcomes of combining ERNN-ECNN, VGG-16, and GoogleNet on the Kaggle repository dataset for picture data detection are shown below.

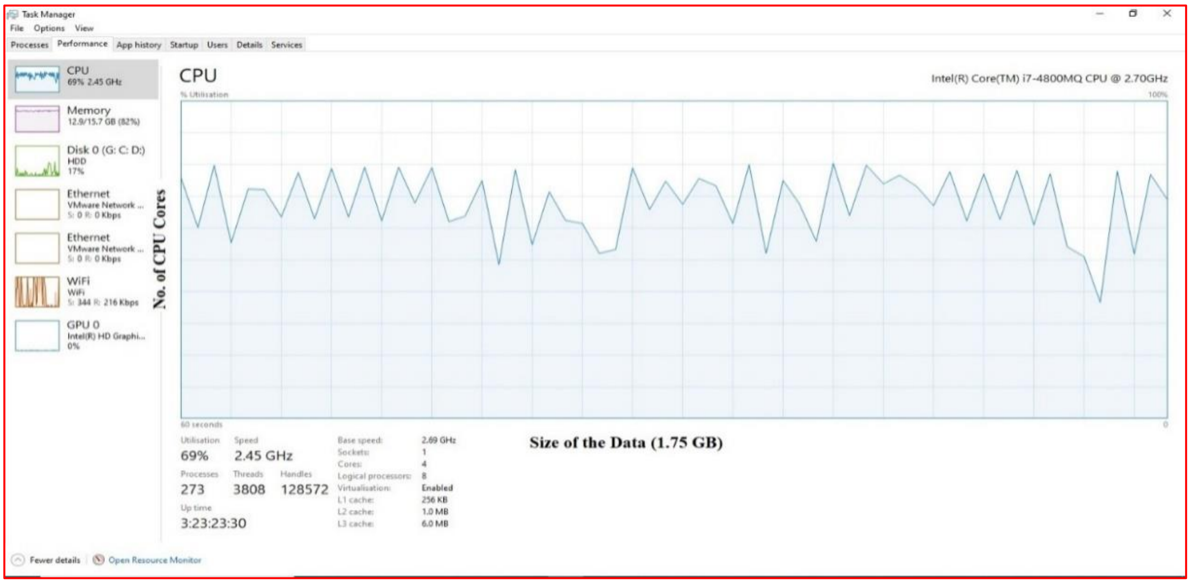

Fig. 4: Utilization of CPU resources in the Google, UCI, and Kaggle datasets for skin cancer CT-scan image data.

While running of experiment on skin cancer image dataset by using ECNN-ERNN deep learning techniques showing CPU utilization in the above figure 4.

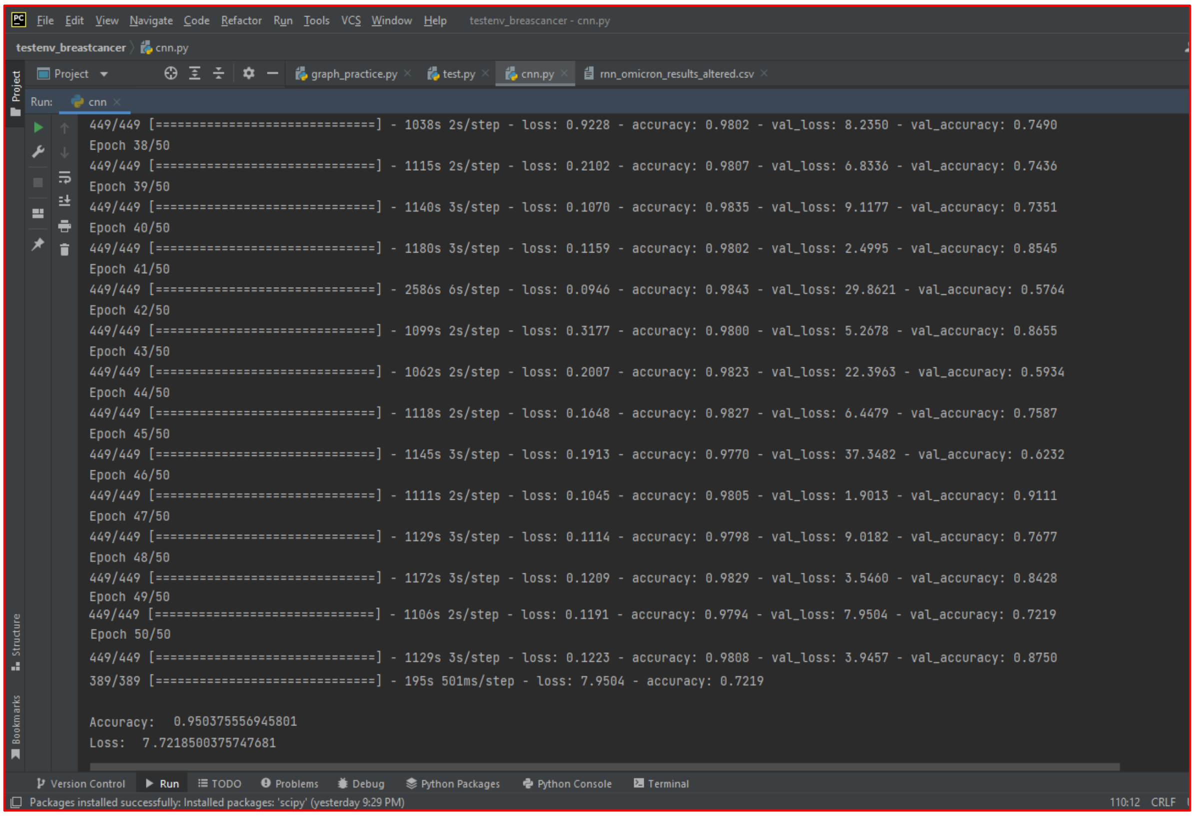

Fig. 5: ECNN stream execution on dataset preparation and testing

Figure 5 depicts the implementation flow across periods on the Skin Cancer dataset, which classifies events as negative or positive.

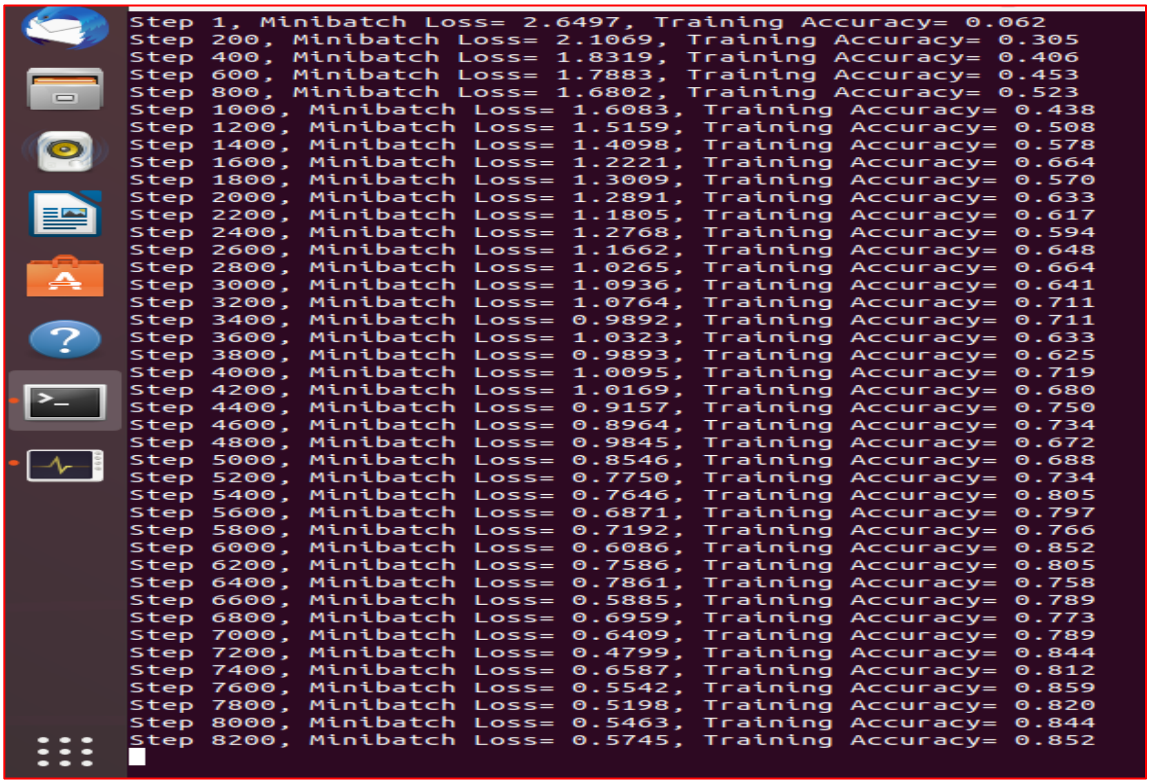

Fig.6: Applying the test dataset to run the ERNN flow

Figure 6 depicts the iterative execution flow of the ERNN method applied to the Skin Cancer dataset used by the projected model.

Evaluation Methods of Performance

To estimate and display the overall trial outcome, the most generally utilized factual approaches, such as precision, correctness, appraisal, F1-score, reaction, and fastidiousness, are applied. Since the limited number of cases in Study One, the quantifiable results are spoken with a 94.02% inevitability range. This is followed by lately published work, which also made use of a limited dataset [20, 23]. Skin cancer may be classed as true optimistic (Tp) or true undesirable (Tn) if persons are precisely examined in our dataset, or it may be classified as untrue optimistic (Fp) or untrue desirable (Fn) uncertainty misdiagnosed. The nuances listed below describe the assigned measurable measurements.

Accuracy:

It is the number of unique occurrences that have been identified in each instance that has been reported. When employing the associated methods, precision is not completely established:

$$Accuracy = \frac{\mathrm{Tp} + \mathrm{Tn}}{\mathrm{Fn} + \mathrm{Tp} + \mathrm{Fp} + \mathrm{Tn}}$$

Precision:

It is calculated as the fraction of obviously projected anticipated good outcomes.

$$Precision = \frac{Tp}{Fp + Tp}$$

Recall:

The number of important outcomes that are accurately distinguished by the calculation is referred to as recall.

$$Recall = \frac{Tp}{Fp + Tn}$$

Sensitivity:

The following measures of responsiveness can be used to determine whether a response is responsive:

$$Sensitivity = \frac{Tp}{Fn + Tp}$$

Specificity:

Using the formulas provided, it identifies the number of precisely perceived and determined certified negatives:

$$Specificity = \frac{Tn}{Fp + Tn}$$

F1-Score:

It is the perfect balance of audit and precision. The maximum likely F score is 1, which indicates exceptional audit accuracy.

$$F1 - Score = 2x \frac{Recall\ x\ Precision}{Recall + Precision}$$

AUC - Area under Curve:

The way to activate the models in more promising situations is discussed in the AUC. Using the associated function listed below, AUC can be resolved:

$$AUC = \frac{Xp\left(\frac{Xp + 1}{2}\right) - \Sigma ri(Xp)}{Xn + Xp}$$

Metrics Evaluation

The proposed model used the going with systems to show and assess the effects of our suggested strategy on ERNN-ECNN strategies for the DL method. To investigate the chaos lattice, the terms "actual positive" (AP), "untrue positive" (UP), "actual negative" (AN), and "true negative" (UN) are initially defined in isolation. The no. of cases was appropriately expected due to OP. The following metrics are units of measurement for evaluation methods used to predict the projected model's quality, precision, callback, and F-measure.

Quality:

The Quality metrics are used to evaluate the value and performance of the research's services, procedures, and quality.

$$Quality = \frac{BP + VM}{BP + VP + BM + VM}$$

Preciseness:
A binary classifier's precision is a metric that determines whether all positive labels are accurate. A twofold classifier gives only two outcome values (for instance sure and negative).

$$Preciseness = \frac{BP}{VP + VM}$$

Callback:
An object that can act at a variety of training stages (like at the beginning or end of an era, before or after a single batch, etc.) referred to as a callback.

$$Callback = \frac{BP}{BP + VM}$$

F-Measure:
In binary classification statistical analysis, the F-score or F-measure of a test is used to measure its accuracy.

$$F - measure = \frac{2 * Preciseness * Callback}{Preciseness + Callback}$$

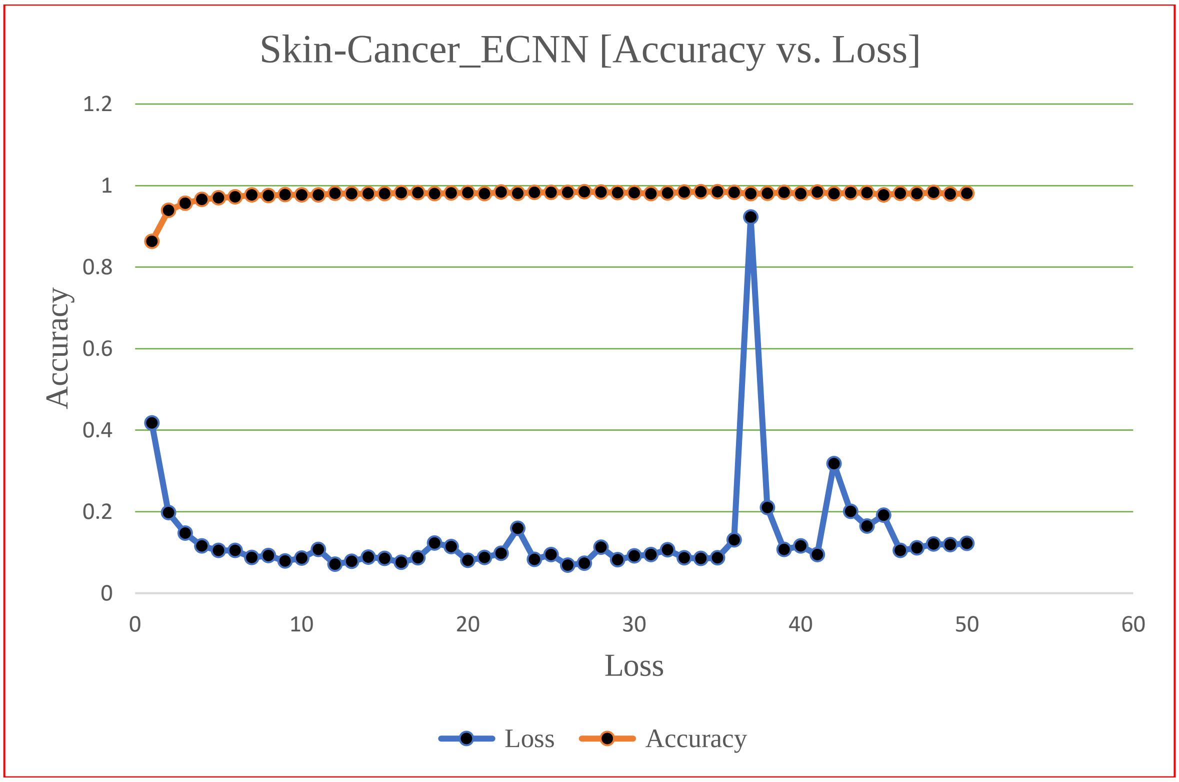

Fig.7: Accuracy versus loss in ECNN data for skin cancer

Figure 7 shows the time intervals that passed between Accuracy and Loss checks on the Skin Cancer dataset.

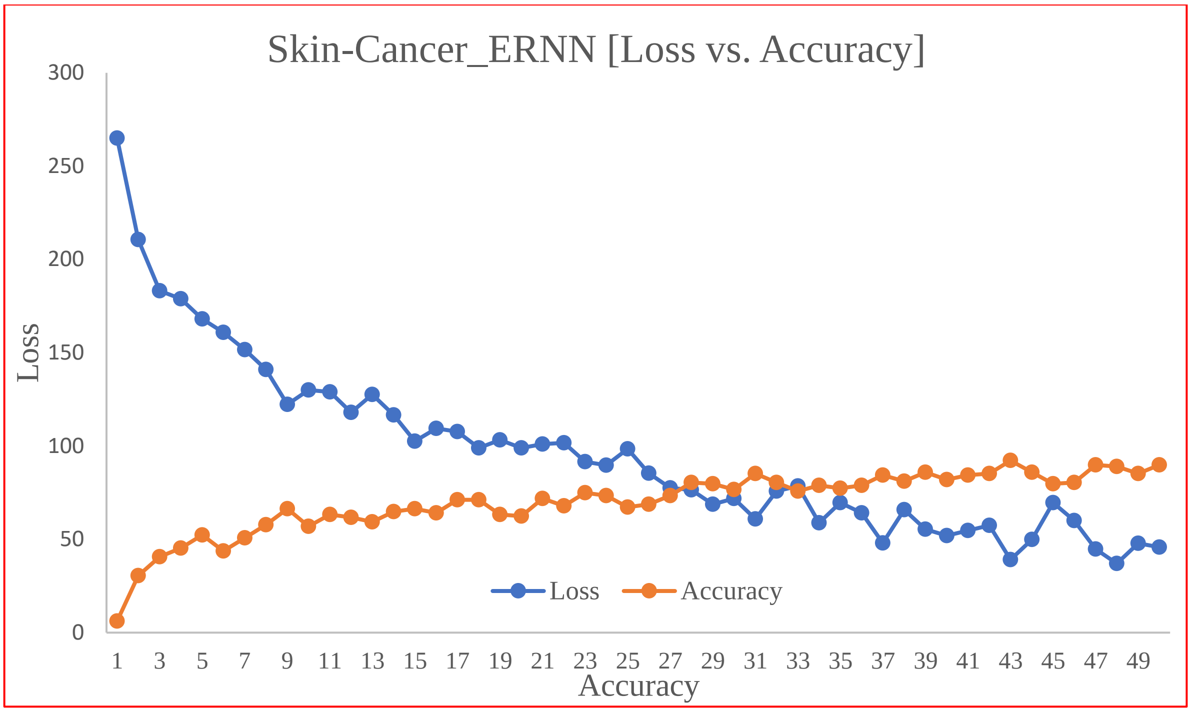

Fig. 8: Skin Malignant growth sickness ERNN information Exactness versus Misfortune

The execution epochs on the Skin Cancer testing and training dataset are depicted in Figure 8. These epochs are located between Accuracy and Loss.

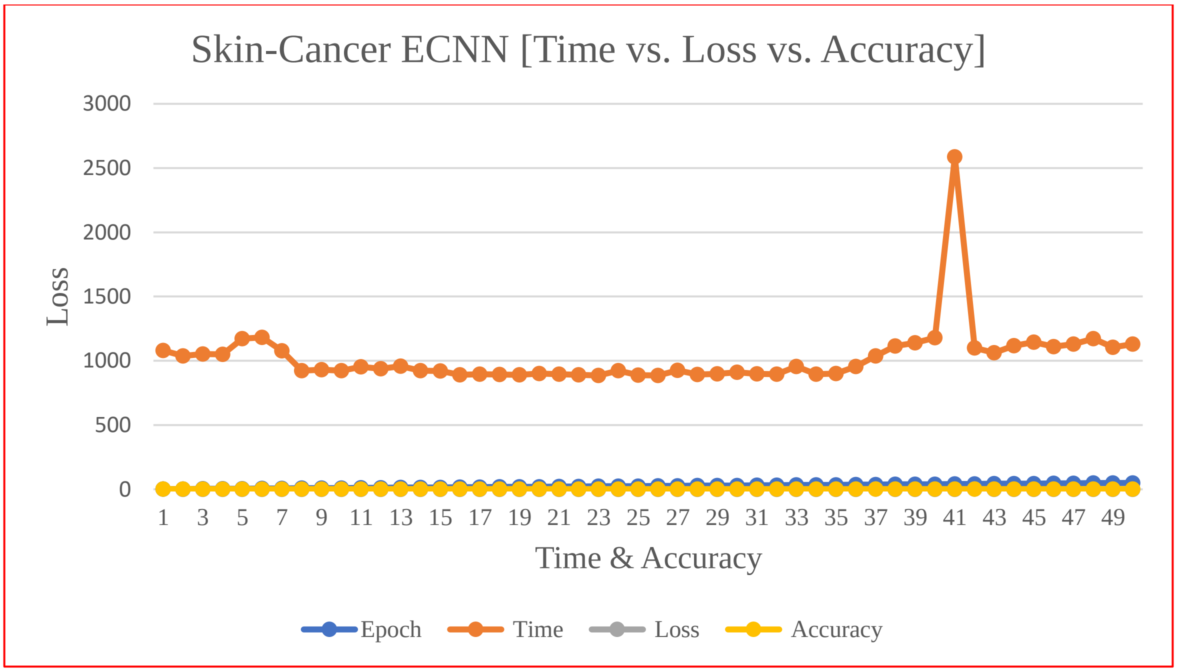

Fig. 9: Skin Malignant growth illness ECNN information Exactness versus Time

Figure 9 illustrates the execution epochs between Accuracy and Loss in relation to a time constraint to predict the proposed model's accuracy.

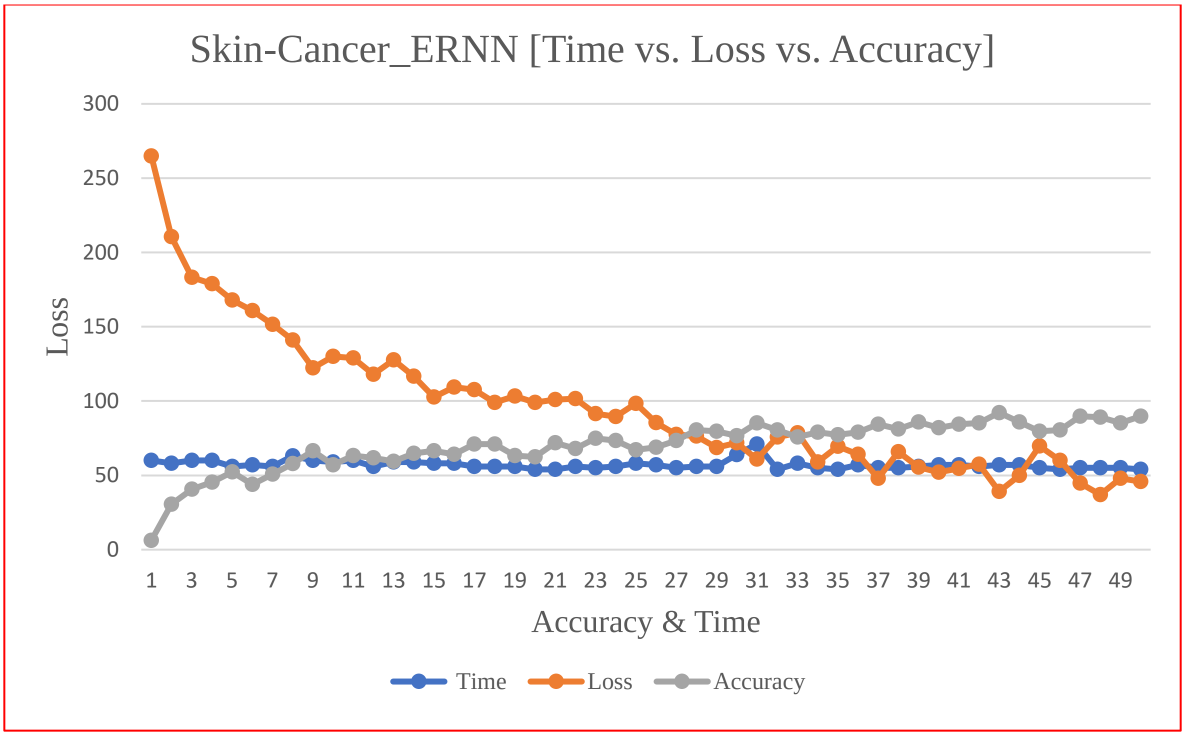

Fig. 10: Accuracy vs. Loss vs. Time: ERNN data on skin cancer

The above figure 10 explains the loss vs time vs accuracy parameters comparison on skin cancer image dataset by using deep learning techniques i.e., ECNN-ERNN approach.

The following table explains how the proposed techniques are compared to various parameters.

Comparison Table

The following table explains how the proposed techniques are compared to various parameters:

Table 5: Metrics compared using ECNN and ERNN techniques

S. No.	The parameter's name	ERNN	ECNN
1.	Execution time	1250 ms	1025ms
2.	Rate of error	0.56	0.14
3.	Loss Value	3.92	2.88
4.	Accuracy Value	0.79	0.97
5.	Dataset size	1.55 GB	1.55 GB
6.	Epochs	30	30
7.	Complexity time	$O(n^2)$	$O(n^2)$
8.	Accuracy	87.32%	94.02%

Based on multiple parameters, the comparison factors of the two methods are described in Table 5. The table comparison with accuracy is 87.32 of ERNN vs 94.02 of ECNN, time complexity is $O(n^2)$ of both proposed techniques of ERNN-ECNN approaches.

Time Complexity

Our method, it has been noted, necessitates more speculation than other systems currently in use. Utilizing a tensor dealing with the unit (TPU) and a reasonable planning unit (GPU) can significantly shorten this time. Additionally, the structure's presentation influences the amount of time required to complete this task. At long last, structure execution is coordinated by framework programming and design gear.

```
"C:\Users\Tarkeshwar Barua\PycharmProjects\neural_network\venv\Scripts\python.exe" "C:/Users/Tarkeshwar Barua/PycharmProjects/neural_network/CNN.py"
2021-09-17 21:29:57.069577: I tensorflow/core/platform/cpu_feature_guard.cc:142] This TensorFlow binary is optimized with oneAPI Deep Neural Network Library (oneDNN) tc
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2021-09-17 21:29:57.070942: I tensorflow/core/common_runtime/process_util.cc:146] Creating new thread pool with default inter op setting: 2. Tune using inter_op_paralle
Found 257 images belonging to 2 classes.
Found 257 images belonging to 2 classes.
2021-09-17 21:29:59.062602: I tensorflow/compiler/mlir/mlir_graph_optimization_pass.cc:176] None of the MLIR Optimization Passes are enabled (registered 2)
Epoch 1/20
257/257 [==============================] - 47s 112ms/step - loss: 0.6168 - accuracy: 0.8590 - val_loss: 0.3229 - val_accuracy: 0.9066
Epoch 2/20
257/257 [==============================] - 29s 113ms/step - loss: 0.4574 - accuracy: 0.8965 - val_loss: 0.4245 - val_accuracy: 0.9066
Epoch 3/20
257/257 [==============================] - 29s 113ms/step - loss: 0.4583 - accuracy: 0.9015 - val_loss: 0.3177 - val_accuracy: 0.9066
Epoch 4/20
257/257 [==============================] - 31s 122ms/step - loss: 0.3668 - accuracy: 0.9104 - val_loss: 0.3076 - val_accuracy: 0.9066
Epoch 5/20
257/257 [==============================] - 30s 118ms/step - loss: 0.4040 - accuracy: 0.9053 - val_loss: 0.3175 - val_accuracy: 0.9066
Epoch 6/20
257/257 [==============================] - 30s 115ms/step - loss: 0.3259 - accuracy: 0.9306 - val_loss: 0.7509 - val_accuracy: 0.9066
Epoch 7/20
257/257 [==============================] - 30s 116ms/step - loss: 0.4376 - accuracy: 0.9137 - val_loss: 0.3075 - val_accuracy: 0.9066
Epoch 8/20
257/257 [==============================] - 31s 119ms/step - loss: 0.3255 - accuracy: 0.9243 - val_loss: 0.3200 - val_accuracy: 0.9066
Epoch 9/20
257/257 [==============================] - 33s 128ms/step - loss: 0.3530 - accuracy: 0.9201 - val_loss: 0.4086 - val_accuracy: 0.9066
Epoch 10/20
257/257 [==============================] - 31s 120ms/step - loss: 0.4048 - accuracy: 0.8959 - val_loss: 0.3208 - val_accuracy: 0.9066
Epoch 11/20
257/257 [==============================] - 31s 120ms/step - loss: 0.2951 - accuracy: 0.9351 - val_loss: 0.3342 - val_accuracy: 0.9066
Epoch 12/20
257/257 [==============================] - 32s 126ms/step - loss: 0.4144 - accuracy: 0.8817 - val_loss: 0.3380 - val_accuracy: 0.9066
Epoch 13/20
257/257 [==============================] - 32s 123ms/step - loss: 0.4278 - accuracy: 0.8889 - val_loss: 0.4086 - val_accuracy: 0.9066
Epoch 14/20
257/257 [==============================] - 34s 134ms/step - loss: 0.4457 - accuracy: 0.8901 - val_loss: 0.3255 - val_accuracy: 0.9066
Epoch 15/20
```

Fig 11: Makes sense of the Last result of the Skin Disease CT-examine picture informational collection from the Kaggle dataset.

The above figure 11 describes the number of epochs with accuracy is 87.32 of ERNN vs 94.02 of ECNN, time complexity is $O(n^2)$ of both proposed techniques of ERNN-ECNN approaches.

The hybrid ECNN-ERNN training and testing model has an accuracy of 95.35 percent and has room for improvement over several other models.

CONCLUSION

In this proposed research strategy, two classifications were employed, positive and negative, for the prediction of the error ratio and accuracy on 660 skin cancer patients' CT-scan images (hybrid ECNN-ERNN techniques). The proposed prototype employs ECNN-ERNN techniques of DL approaches to discover processes with improved reduced error and accuracy rates during the assessment, identification, and prediction procedures for skin cancer infection. In terms of parameters and measurements like accuracy, the new model performed better than the previous system (94.02%), error rate (0.13), val-loss (3.94), and val-accuracy (0.87). The number of epochs (30), the temporal complexity (O (n2)), and the execution time. In conclusion, we determined that the hybrid ECNN-ERNN model performed better in terms of precision during the analysis (87.32 %), error rate (0.56), loss value (3.92), accuracy value (0.79), and the size of the dataset on the disc used in this study when compared to the previous system (1.55 GB). The number of epochs (30), the time complexity (O(n2), and the duration (1025 milliseconds). The proposed model can be improved and used to anticipate and detect effective cases in a couple of seconds by including an IoT-based resilient mechanism. This approach has a promising future based on the framework that is employed and coupled to generate the required results.

REFERENCES

[1] ZaferCivelek et al.,"An Improved Deep CNN for an Early and Accurate Skin Cancer Detection, and Diagnosis System", International Journal of Engineering Research and Development, UluslararasıMühendislik, Araştırma ve GeliştirmeDergisi, UMAGD, (2022) 14(2), 721-734, Cilt/Volume:14 Sayı/Issue:2 Temmuz/July 2022, DOI: 10.29137/umagd.116295

[2] MdShahin Ali et al., "An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models", Machine Learning with Applications 5 (2021) 100036, https://doi.org/10.1016/j.mlwa.2021.100036,

[3] S. Haggenmu¨ller et al. / European Journal of Cancer 156 (2021) 202e216, "Skin cancer classification via convolutional neural networks: systematic review of studies involving human experts", https://doi.org/10.1016/j.ejca.2021.06.0490959-8049/ª 2021 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

[4] Boman, J., &Volminger, A. (2018). Evaluating a deep convolutional neural network for classification of skin cancer. In.

[5] Bray, F., Ferlay, J., Soerjomataram, I., Siegel, R. L., Torre, L. A., & Jemal, A. (2018). Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: a cancer journal for clinicians, 68(6), 394-424.

[6] Brekhna, B., Mahmood, A., Zhou, Y., & Zhang, C. (2017). Robustness analysis of superpixel algorithms to image blur, additive Gaussian noise, and impulse noise. Journal of Electronic Imaging, 26(6), 061604.

[7] Daghrir, J., Tlig, L., Bouchouicha, M., & Sayadi, M. (2020). Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. Paper presented at the 2020 5th international conference on advanced technologies for signal and image processing (ATSIP).

[8] Dorj, U.-O., Lee, K.-K., Choi, J.-Y., & Lee, M. (2018). The skin cancer classification using deep convolutional neural network. Multimedia Tools and Applications, 77(8), 9909-9924. Gedraite, E. S., &Hadad, M. (2011). Investigation on the effect of a Gaussian Blur in image filtering and segmentation. Paper presented at the Proceedings ELMAR-2011.

[9] Mahbod A, Schaefer C, Ellinger I, Ecker R, Pitiot A, Wang C. Fusing fine-tuned deep features for skin lesion classification. Comput Med Imaging Graph 2019; 71:19e29. Https://doi.org/10.1016/j.compmedimag.2018.10.007.

[10] Salerni G, Tera´n T, Puig S, Malvehy J, Zalaudek I, Argenziano G, et al. Meta-analysis of digital dermoscopy followup of melanocytic skin lesions: a study on behalf of the International Dermoscopy Society. J EurAcadDermatolVenereol 2013; 27:805e14.

[11] Vestergaard ME, Macaskill P, Holt PE, and Menzies SW. Dermoscopy compared with naked eye examination for the diagnosis of primary melanoma: a meta-analysis of studies performed in a clinical setting. Br J Dermatol2008; 159:669e76.

[12] Haenssle HA, Fink C, Schneiderbauer R, Toberer F, Buhl T, Blum A, et al. Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Ann Oncol2018; 29:1836e42.

[13] Lodha S, Saggar S, Celebi JT, Silvers DN. Discordance in the histopathologic diagnosis of difficult melanocytic neoplasms in the clinical setting. J CutanPathol2008; 35:349e52.

[14] Corona R, Mele A, Amini M, De Rosa G, Coppola G, Piccardi P, et al. Interobserver variability on the histopathologic diagnosis of cutaneous melanoma and other pigmented skin lesions. J ClinOncol1996; 14:1218e23.

[15] Tschandl P, Rosendahl C, Akay BN, Argenziano G, Blum A, Braun RP, et al. Expert-level diagnosis of nonpigmented skin cancer by combined convolutional neural networks. JAMA Dermatol2019; 155:58e65.

[16] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017; 542:115e8.

[17] Nasr-Esfahani E, Samavi S, Karimi N, Soroushmehr SMR, Jafari MH, Ward K, et al. Melanoma detection by analysis of clinical images using convolutional neural network. In: 2016 38th annual international conference of the IEEE engineering in medicine and biology society. EMBC; 2016. p. 1373e6.

[18] Al-Masni, M. A., Al-Antari, M. A., Choi, M.-T., Han, S.-M., & Kim, T.-S. (2018). Skin lesion segmentation in dermoscopy images via deep full resolution convolutional networks. Computer Methods and Programs in Biomedicine, 162, 221–231.

[19] Alfed, N., Khelifi, F., Bouridane, A., &Seker, H. (2015). Pigment network-based skin cancer detection. In 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC) (pp. 7214–7217). IEEE.

[20] Aljanabi, M., Özok, Y. E., Rahebi, J., & Abdullah, A. S. (2018). Skin lesion segmentation method for dermoscopy images using artificial bee colony algorithm. Symmetry, 10(8), 347. Biessmann, F., Salinas, D., Schelter, S., Schmidt, P., & Lange, D. (2018). ''Deep" learning for missing value imputation in tables with non-numerical data. In Proceedings of the 27th ACM international conference on information and knowledge management (pp. 2017–2025).

[21] Canadian Cancer Society's Advisory Committee on Cancer Statistics (2014). Canadian cancer statistics 2014 - special topic: Skin cancers. Retrieved from https://www. Cancer.ca/statistics. (Accessed 30 December 2020).

[22] Cancer Council Australia (2018). Understanding skin cancer - a guide for people with cancer, their families, and friends. Retrieved from https://www.cancer.org. au/about-cancer/types-of-cancer/skin-cancer.html. (Accessed 30 December 2020).

[23] Ravikumar CV, Kala Praveen Bagadi, Design of MC-CDMA receiver using RBF network to mitigate MAI and nonlinear distortion, Neural Computing and Applications, Vol.31, Issue 2, 2019.

[24] Ravikumar CV, Kala Praveen Bagadi, MC-CDMA receiver design using recurrent neural network for eliminating MAI and non-linear distortion, International Journal of Communication Systems (IJCS), Vol.10 , Issue 16, 2017.

[25] K. Bagadi et al., "Detection of Signals in MC–CDMA Using a Novel Iterative Block Decision Feedback Equalizer," in IEEE Access, vol. 10, pp. 105674-105684, 2022, doi: 10.1109/ACCESS.2022.3211392.

[26] Asadi Srinivasulu, Rajesh, A., Olutayo Oyeyemi Oyerinde, "Performance and Improvement Analysis of the Underwater WSN Using a Diverse Routing Protocol Approach", Journal of Computer Networks and Communications, vol. 2022, Article ID 9418392, 19 pages, 2022. https://doi.org/10.1155/2022/9418392.

[27] K, S.; CV, R.; A, R.; Pau, G. Underwater Wireless Sensor Network Performance Analysis Using Diverse Routing Protocols. J. Sens. Actuator Netw. 2022, 11, 64. https://doi.org/10.3390/jsan11040064.

[28] Sathish, K.; Anbazhagan, R.; Venkata, R.C.; Arena, F.; Pau, G. Investigation and Numerical Simulation of the Acoustic Target Strength of the Underwater Submarine Vehicle. *Inventions* 2022, *7*, 111. https://doi.org/10.3390/inventions7040111.

[29] Xiangjie Kong, Zhiqiang Huang, Guojiang Shen, Hang Lin, Mingjie Lv. "Urban Overtourism Detection Based on Graph Temporal Convolutional Networks" IEEE Transactions on Computational Social Systems 2022. DOI: 10.1109/TCSS.2022.3226177.

[30] Xiangjie Kong, Yuhan Wu, Hui Wang, and Feng Xia. "Edge Computing for Internet of Everything: A Survey." IEEE Internet of Things Journal 9, no. (23), pp.23472–23485, 2022.

[31] Xiangjie Kong, Qiao Chen, MingliangHou, Azizur Rahim, Kai Ma, and Feng Xia. "RMGen: A Tri-Layer Vehicular Trajectory Data Generation Model Exploring Urban Region Division and Mobility Pattern." IEEE Transactions on Vehicular Technology 71, no. (9), pp.9225–9238, 2022.

[32] Xiangjie Kong, Ning Li, Chenwei Zhang, Guojiang Shen, Zhaolong Ning, and Tie Qiu. "Multi-Feature Representation based COVID-19 Risk Stage Evaluation with Transfer Learning." IEEE Transactions on Network Science and Engineering 9, no. (3), pp.1359–1375, 2022.

[33] Xiangjie Kong, Kailai Wang, Shupeng Wang, Xiaojie Wang, Xin Jiang, Yi Guo, Guojiang Shen, Xin Chen, and Qichao Ni, Real-time Mask Identification for COVID-19: An Edge Computing-based Deep Learning Framework. IEEE Internet of Things Journal8, no. (21), pp.15929-15938, 2021.

[34] Xiangjie Kong, Bing Zhu, Guojiang Shen, TewabechekoleWorkneh, Zhanhao Ji, Yang Chen, and Zhi Liu. "Spatial-Temporal-Cost Combination based Taxi Driving Fraud Detection for Collaborative Internet of Vehicles." IEEE Transactions on Industrial Informatics 18, no. (5), pp.3426–3436, 2022.

[35] Xiangjie Kong, GaohuiDuan, MingliangHou, Guojiang Shen, Hui Wang, Xiaoran Yan, and Mario Collotta, Deep Reinforcement Learning based Energy Efficient Edge Computing for Internet of Vehicles. IEEE Transactions on Industrial Informatics18, no. (9), pp.6308–6316, 2022.

[36] Xiangjie Kong, Kailai Wang, MingliangHou, XinyuHao, Guojiang Shen, Xin Chen, Feng Xia, A Federated Learning-based License Plate Recognition Scheme for 5G-enabled Internet of Vehicles, IEEE Transactions on Industrial Informatics 17, no. (12), pp.8523–8530, 2021.

[37] Xiangjie Kong, HaoranGAO, Guojiang Shen, GaohuiDuan, Sajal K. Das, FedVCP: A Federated Learning based Cooperative Positioning Scheme for Social Internet of Vehicles, IEEE Transactions on Computational Social Systems9, no. (1), pp.197–206, 2022

[38] Guojiang Shen, Xiao Han, KwaiSang Chin, and Xiangjie Kong. "An Attention-Based Digraph Convolution Network Enabled Framework for Congestion Recognition in Three-Dimensional Road Networks." IEEE Transactions on Intelligent Transportation Systems23, no. (9), pp.14413–14426, 2022.