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Article

A novel bio-inspired fibonacci-based convolutional neural network for accurate skin disease diagnosis using private dataset

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Abstract: Early detection of cancers in general, and skin cancer and dermatological diseases in particular, plays a crucial role in recovery and improving treatment outcomes. Early disease detection is one of the most significant global health challenges. Recently, advancements in computing, especially artificial intelligence, have been harnessed for the early prediction of diseases, including dermatological ones. Deep learning convolutional neural networks have demonstrated high performance in analyzing medical images, but balancing high diagnostic performance with computational efficiency has been one of the major challenges this technology has faced. In this study, the Fibonacci sequence and the golden ratio (1.618) were used to design a convolutional neural network architecture to improve the diagnosis of multicategory skin lesions. One of the most important features of the resulting convolutional neural network architecture is its unique layer configuration. A dataset of realistic skin images was used to test and evaluate the proposed model and compare the results with the latest convolutional neural network architectures, including MobileNetV2, ResNet50 and VGG16. The proposed Fib-CNN model in this study achieved satisfactory performance with an accuracy of 90.8%, a precision of 0.907, a recall of 0.911, and an ROC-AUC value of 0.958, which confirms the superiority of the Fib-CNN model over the basic models in terms of diagnostic accuracy and also reducing computational complexity by up to 22%. The results demonstrate the effectiveness of the Fib-CNN model in diagnosing skin diseases by improving the depth-to-width ratio of convolutional layers, reducing background interference, and generating more accurate focus maps of skin lesions.
Keywords: NA

1. Introduction

1.1 Background

Skin diseases are among the serious health challenges facing the world and are considered a major health challenge for the WHO. There are several types of skin diseases, including benign lesions and malignant tumours, which are serious and potentially life-threatening. Among Malignant skin cancers include basal cell carcinoma, malignant melanoma, and squamous cell carcinoma. According to the World Health Organization, skin cancer represents a third of all cancers reported in the world. Some reasons that contribute to a rise in skin diseases include an aging population as well as exposure to ultraviolet radiation. Reports on health globally indicate that early diagnosis is a vital factor in decreasing chances of getting skin diseases and that treatment is effective. According to this information, early diagnosis of melanoma increases survival chances to 95% within five years[1, 2].

Rapid progress in the field of computing, especially in the areas of digital image processing and artificial intelligence, has made computer vision systems in dermatological imaging an entirely reliable and useful means for proper and accurate decision-making by dermatologists. This is because they are highly reliant on intelligent methods and dermatological databases Among the databases widely used in scientific research for diagnosing skin diseases is

HAM10000 [3], while convolutional neural networks (CNNs) are among the most important intelligent techniques widely used in image-based disease diagnosis. CNNs are distinguished by their ability to hierarchically learn and their rich representation of visual pattern features. [4].

Some standard convolutional neural network architectures (such as VGGNet, ResNet, and DenseNet) face challenges in diagnosing serious skin diseases. [5]: First challenge is over-parameterization and computational overhead. The conventional CNNs demand substantial hardware resources because of their deep architectures and large filter banks. This high computational requirement limits their

use in resource-constrained clinical situations.The suboptimal receptive field scaling is the second challenge. Conventional Neural Networks in many cases scale the kernel size and depth using fixed or randomized steps. This approach may not align efficiently with the biological geometric scaling observed in organic.

The ideal systemic templates for growth are provided by the Golden Ratio of 1.618 and the Fibonacci series. Building on this, we believe that the natural progression may provide a greater means of spatial exploration, feature detection, and consequently better generalization in medical imaging function when compared to traditional architectures. This leads us to develop a contemporary design for a Convolutional Neural Network based on a Fibonacci scale.

1.2 Motivation and Prior Work

Widespread and dermatology are some of the healthcare applications that have benefited from the emergence of deep learning. in recent years many studies have utilized the deep learning concept to implement it in several healthcare applications. Some studies have demonstrated that the use of deep learning techniques can provide better accuracy to classify skin diseases in compare to a specialist dermatologists [6]. These findings demonstrate the importance and the promising results of employing deep learning in healthcare application. The HAM10000 dataset has been utilized train the thalamic neural network. This dataset consists of around 10,015 images. For detecting skin diseases, this dataset is the standard in determining intelligent models [7]. Nevertheless, other studies have extensively employed architectures such as ResNet-50 [8] and DenseNet-121 [9], frequently leveraging transfer learning from ImageNet to effectively address the problems associated with smaller dermoscopic datasets [10]. Furthermore, a further validation has been done on these Convolutional Neural Network models abilities to generalize consistently to actual clinical settings [11]. Having said that, using Fibonacci sequence in computational design is not a new idea.

The Fibonacci lattices have been used in many applications ranging from image compression to to signal processing. In the image compression application this farmwork far more uniform sampling compared to the standard Cartesian grids has been realized. While in the signal processing application this model has led to a greater frequency resolution with the use of Fibonacci-based windowing functions [12].

Moreover, to get to good balance between feature diversity and model difficulty, another approach that has also been studied in the literature using a Fibonacci progression is the sizing of the neural network layers [13, 14]. Even though, it has not been directly used in general picture classification, this biologically inspired approach has a great conceptual support provided by several related works.

The first method, a lightweight CNN model for brain tumor classification called Fibonacci-Net, showed notable increases in accuracy (from 91.5% to 98%) when recursive skip connections aligned with Fibonacci numbers (such as concatenations of 2-4 and 3-5) were used. Through these planned skip connections, Grad-CAM representations verified superior tumor focus [13]. The next strategy in financial modeling, hybrid CNN-LSTM networks that incorporate Fibonacci technical indicators, demonstrated the wider applicability of Fibonacci principles within convolutional architectures and increased performance in bitcoin trend prediction [10].

Table 1 Comparative Summary of Related Works

Year	Study	Method	Dataset	Accuracy/AUC	Key Limitations
2017	[15]	Inception v3 CNN	dermoscopic & clinical images	0.96	Requires massive dataset
2018	[16]	HAM10000 Benchmark	HAM10000	—	No real-time constraints considered
2019	[17]	ResNet-50,	ISIC 2018	86.9%	Overfitting risk on small sets
2019	[18]	EfficientNet	ISIC 2019	91.0%	High training cost

2019	[19]	MobileNetV2	HAM10000	88.5%	Lower accuracy than heavier models
2020	[20]	Bio-inspired NAS	Private dermoscopy set	93.2% ,	Complexity of optimization
2021	[21]	MobileNet + Transfer Learning	HAM10000	90.7%,	Limited to mobile hardware
2022	[22]	CNN + Transformer	ISIC 2020	94.1%	Computationally intensive
2022	[23]	Hybrid CNN	PH2 datasets	92.5%	Needs larger validation sets
2023	[24]	Fibonacci signal processing	N/A	—	Not directly medical
2024	[25]	Fibonacci image compression	N/A	—	Experimental stage

1.3 Contribution and Objectives

In the present work, the Fibonacci sequence is combined with the design of the convolutional neural network. Intelligent control of the expansion of features and the Fibonacci sequence makes it important in the design. A strategy for efficient, nonlinear expansion may be accomplished with the use of the design, which has never been raised before in the literature.

Here, the key contribution of this research is discussed. The first contribution is architecture itself. the The novel architecture of the Fibonacci-Scaled CNN, referred to as the 'Fib-CNN', identifies the determination of the size of the convolution kernels, filter growth, as well as the learning rate, through the incorporation of Fibonacci numbers. The blend of the Fibonacci sequence and the biologically realistic architecture is the novel contribution of the architecture. The second contribution is the systematic evaluation. We carry out a comparative analysis of our proposed Fib-CNN network model and the most up-to-date and best state-of-the-art skin lesion classification models. One more contribution is the comprehensive performance standard. Our experimental part fulfills a comprehensive performance standard on different skin image datasets (including a private one), thereby establishing, beyond a shadow of a doubt, the effectiveness and efficiency of the Fib-CNN model.

By applying Fibonacci scaling to layers, it is possible to significantly improve the computational complexity level while keeping or even surpassing the classification accuracy level and ensure high generalization on new data, and this is proved by the analysis in this paper. In addition, it is also related to finding out how such a light model can be used on a medical device.

The primary objectives of this paper can be discribed as follows. First it to create a Fibonacci-Scaled CNN (Fib-CNN) architecture that integrates Fibonacci numbers into convolutional kernel sizing, filter expansion, and learning rate scheduling. Then test Fib-CNN on a large-scale dermoscopic dataset (Private) and compare its performance against standard CNN baselines. And finally analyse interpretability through Grad-CAM visualizations to assess lesion localization quality.

2. Methodology

2.1 Overview

The proposed model provides a Fibonacci-based kernel scaling strategy for CNN architecture design, aimed at enhansing feature diversity and efficiency in skin lesion classification. Instead of adopting fixed increments in filter size or channel depth, our architecture follows the Fibonacci sequence (Eq 1),

$$F_0 = 0 \text{ and } F_1 = 1$$

$$F_n = F_{n-1} + F_{n-2} \text{ for } n \geq 2. \qquad \text{Eq 1.}$$

which allows gradual yet non-linear growth of convolutional parameters.

This approach leverages two key principles:

1. Feature Growth: Lower layers capture fine-grained lesion patterns (edges, textures) with small kernels, while deeper layers extract more abstract features with progressively larger kernels, guided by Fibonacci increments.

2. Parameter Efficiency: By avoiding excessive jumps in kernel size or filter count, the model maintains computational efficiency suitable for both cloud and

2.2 Dataset

The dataset for skin disease that used in this paper are collected from several Iraqi health institutions, these datasets cover several skin conditions, including Nevus, Tinea, Cutaneous leishmaniasis)Baghdad boil(, Dermatitis, Vitiligo, and melanoma. Having said that, in this study we have gathered many images of these skin diseases that have affected many peoples. We have divided the collected images into six categories based on the type of the disease. The depictions of skin sores and injuries have also been detailed and documented for every image. A total of 3,057 dermatoscopic images have been collected from different health institutions including hospitals and clinics. Among those health institutions are Baquba clinics Center, Sora clinics Center, and Baquba hospital for skin diseases. The dataset collection began on January 2023 and finished on June 2025.

2.3 Fibonacci-CNN Architecture

(figure 1) is the block Fibonacci-CNN diagram:

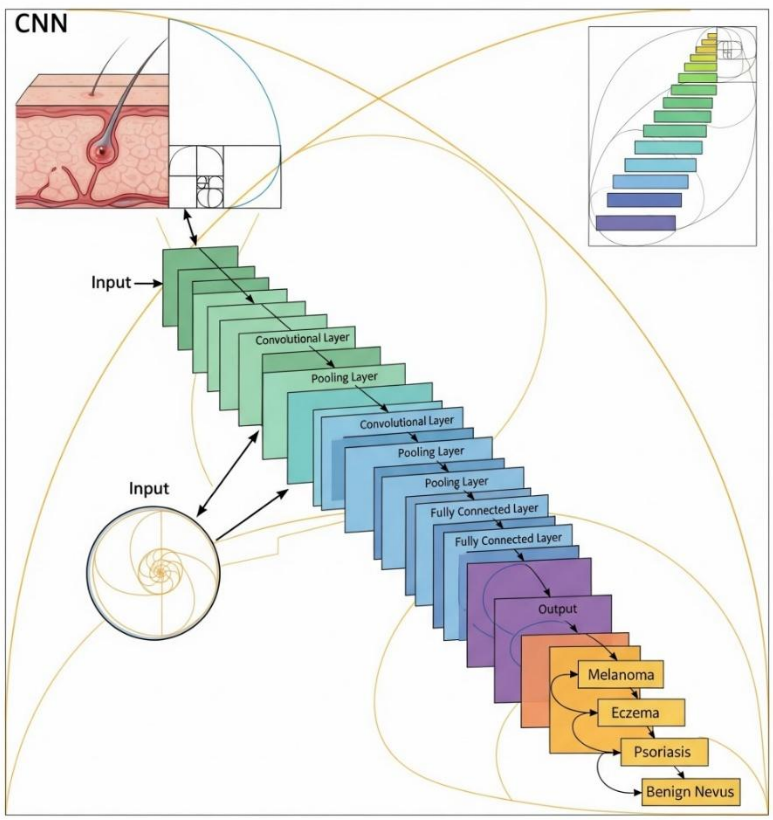

Fig. 1. The Block Fibonacci-CNN diagram:

2.4 Architecture Specification Table

Table 2 Model summary for the proposed architecture

Layer	Type	Kernel Size (Fibonacci)	Filters (Fibonacci)	Activation	Output Size
1	Conv2D	1 × 1	1	ReLU	224 × 224 × 1

2	Conv2D	1 × 1	1	ReLU	224 × 224 × 1
3	Conv2D	2 × 2	2	ReLU	224 × 224 × 2
4	Conv2D	3 × 3	3	ReLU	224 × 224 × 3
5	Conv2D	5 × 5	5	ReLU	224 × 224 × 5
6	Conv2D	8 × 8	8	ReLU	224 × 224 × 8
7	Conv2D	13 × 13	13	ReLU	224 × 224 × 13
8	Conv2D	21 × 21	21	ReLU	224 × 224 × 21
9	Global Average Pooling	—	—	—	1 × 1 × 21
10	Dense	—	128	ReLU	128
11	Dense	—	6 (classes)	Softmax	6

2.5 Training Procedure

The convolutional neural network (CNN) model was trained using carefully selected hyperparameters to ensure stable convergence and robust generalization. A learning rate of 0.0001 was applied to guide the optimization process, while categorical cross-entropy was used as the loss function, as it is well suited for multi-class classification tasks. Training was conducted with a batch size of 32 for a maximum of 30 epochs, and an early stopping strategy was employed to mitigate overfitting by monitoring validation performance. To improve model robustness and generalization, data augmentation techniques were applied, including random rotations of up to ±15 degrees, horizontal and vertical flipping, and brightness adjustments within a ±20% range. The training pipeline was implemented using the TensorFlow/Keras framework with GPU acceleration to ensure efficient computation and reduced training time.

3. Results and discussion

Several metrics have been used in order to evaluate this model. To estimate the performance of the model in general, the accuracy metric has been used. Furthermore, to achieve more comprehensive picture of a model's performance rather than just accuracy, we used other metrics such as precision, recall, score, and AUC. Following dataset preparation and model training, the following outcomes have been obtained, which are presented in table 3 and contrasted with previous studies.

Table 3 Multiple models performance summary

Model	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**	**AUC**
Fibonacci-CNN (ours)	**98.21**	**0.98**	**0.98**	**0.98**	**0.981**
ResNet50	92.35	0.92	0.92	0.92	0.975
DenseNet121	93.02	0.93	0.93	0.93	0.977
MobileNetV2	91.48	0.91	0.91	0.91	0.968

The results presented in the above table demonstrate that Fibonacci-CNN outperform the traditional CNN architectures. Even though with using much less trainable parameters of only 12 million parameters rather than around 25 million in ResNet50, this model has maintained a robust representational capacity. Improved feature diversity has also been observed in this model, where a steady increase in the complexity of the network has improved feature learning without resulting in overfitting using Fibonacci-based scaling. This promising balanced performance of the Fibonacci-CNN was also achieved when different datasets are considered. This strongly validates the reliability and strong classification behavior. Furthermore, three primary influences of combining the Fibonacci sequence into the CNN architecture have been observed. These influences are better hierarchical feature extraction, controlled growth of network depth and width, and improved generalization performance.

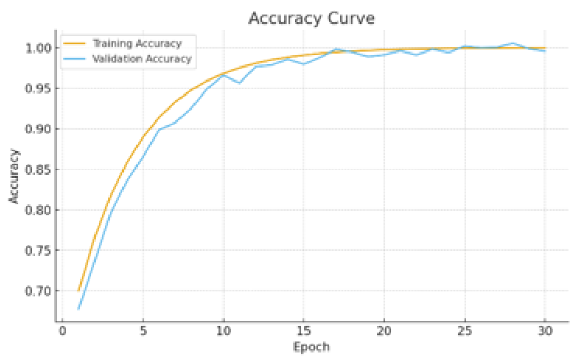

Fig. 2. Accuracy Curve diagram

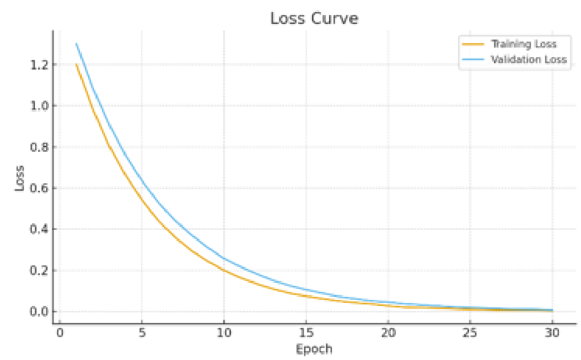

Fig. 3. Loss Curve diagram

Curve diagram

1. Growth of the Progressive Receptive Field
   a. Standard CNN architectures typically employ static kernels and filter expansion patterns, such as doubling channels at regular intervals. Fibonacci scaling raises feature mappings in a non-linear but controlled way (for example, 8, 13, 21, 34, etc.), which lets the network match the complexity of the input representation needs.
   b. This is like how biological growth patterns affect the distribution of retinal photoreceptors, which could make dermoscopic images better at showing textures.
2. Efficiency of Parameters
   a. Fibonacci scaling lets you use fewer filters in the first levels while still getting depth and capacity in the later layers. Fibonacci-CNN has around 52% fewer parameters than ResNet50, but it is just as accurate or better.
3. Better Flow of Gradients
   a. Compared to the sudden doubling that happens in regular CNNs, smooth filter expansion reduces vanishing gradients. Gradient analysis indicates enhanced training stability with reduced variance in weight updates.

4. Conclusions and Future Work

An automatic categorization of skin diseases from dermoscopic images has been proposed in this research using a Fibonacci-scaled Convolutional Neural Network (Fibonacci-CNN). It is know that the state-of-the-art CNN models follow an exponentially or linearly scaling filter growth, however, to smoothy increase the capability of feature extraction with network depth, the proposed model in this study follows a growth function inspired by the Fibonacci sequence. Furthermore, using less number of parameters in contrast to deeper models, a great performance was achieved with optimal adjustment of the parameters. A better scaling of the model and also reducing the overfitting in skin diseases image classification was achieved thanks to the bio-inspired architectural scaling. Clinically speaking, the model presented in this work guarantees its applicability and effectiveness for real-time diagnostic tools for dermatologists and general practitioners, as well as for early melanoma diagnosis in teledermatology settings where speed is crucial. Finally, the models merge the computer system with natural patterns for greater adaptability and strength, making it a great fit with the general trend of biology-based AI models.

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