

Automated Skin Cancer Detection: Leveraging Hyperband for Optimized Convolutional Neural Networks

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Abstract:

Skin cancer is an extremely common disease around the world and proactive identification is key to raising survival rates. The area of study of skin cancer detection offers a compelling use case for the application of artificial intelligence (AI) within the domain of image-based diagnosis. Through the analysis of large datasets, AI algorithms have the capacity to classify clinical images with remarkable accuracy. Convolutional Neural Networks (CNNs) have proven to be effective as dermatologists in diagnosing skin lesions. However, conventional hyperparameter tuning techniques like manual selection or grid search are computationally intensive and time consuming. This work utilizes Hyperband which is an adaptive optimization algorithm to optimize significant parameters like learning rate, dropout rate, and batch size efficiently on datasets like HAM10000, ISIC Archive, and Kaggle's Skin Cancer dataset. The proposed framework of Hyperband optimization has resulted in an increased accuracy of 92.8% in terms of skin cancer detection. Hyperband-optimized CNNs outperformed baseline models by dynamically allocating resources and removing poor configurations in a quick time. The work presents the hyperband model with improved accuracy, precision, recall, F1-score, and AUC-ROC scores and significantly lower computational overhead. These results prove the revolutionizing potential of automated hyperparameter optimization platforms in enhancing AI-assisted medical diagnosis, and providing scalable and highly efficient solutions for early skin cancer detection.

Keywords: Convolutional Neural Networks, Hyperband Optimization, Medical Image Classification, Automated Hyperparameter Tuning, Deep Learning

1. Introduction

One of the greatest health risks to the general population is Skin Cancer. It requires utmost care and caution should be taken because there has been a steep rise in the incidence rate all over the world. It is the most prevalent type of cancer with different types like melanoma, basal cell carcinoma, and squamous cell carcinoma. Since this cancer is highly curable if a person gets diagnosed early, it is suggested to be diagnosed early so that one can be given the best treatment. At the same time, it relies on very well-trained dermatologists to undertake a visual examination of skin lesions. Such a process is thus time-consuming and prone to errors, especially in peak seasons. Connected to this is a major disabler to early screening: dermatologists are few and thin on the ground in remote rural or underserved areas [1][11].

However, the combination of machine learning with medicine is endowing novel avenues to tackle these issues. Deep learning algorithms have the empowering abilities of automation in diagnosis by pairing the expertise of the dermatologist with timely accuracy in diagnosing skin

lesion diagnosis [22][2]. Such deep networks such as convolutional neural networks, beside their application to such tasks as skin lesion classification and detection, have further shown great usefulness in medical image analysis [1][7].

Such technologies promise to democratize health care by bringing skin cancer diagnosis equivalent to the very poor communities. Some of the databases used to provide diverse dermatological image resources for AI training include HAM10000 [11], ISIC Archive [14], and Kaggle's Skin Cancer MNIST dataset [13]. Architectures like TensorFlow [19] and PyTorch [21] have efficiently propelled progress in the model's propagation in addition to the development and deployment of such systems. CNN models such as ResNet [7], and Inception have greatly enhanced diagnostic accuracy. Such models thereby utilize deep hierarchical representation of features to try and understand very faint patterns from medical images making them more precise. In addition, model training and the model architecture have been enabled by libraries such as Keras [20] and optimizers like Adam [10], and therefore they are more effective.

The AI solutions supported by big datasets and cutting-edge deep learning technology are an economical solution to the plight of skin cancer detection. Through their implementation, the healthcare systems have the capability to provide early and precise diagnosis and further reduce the burden of global skin cancer and enhance outcomes for patients.

The research tackles the hyperparameter optimization problem in CNNs related to skin cancer detection with the Hyperband technique. Hyperband is a very robust methodology for hyperparameter optimization. Hyperband is a fast algorithm to optimize appearances of CNN because of its higher efficiency over other broad approaches. This current piece of work is aimed at the following:

- i) Hyperparameter Optimization Using Hyperband** - To optimize significant hyper parameters, including batch size and dropout rates, for CNN models used in skin lesion classification.
- ii) Performance Evaluation and Comparison** - CNN models optimized with Hyperband will be compared against baseline models, which are those with handpicked hyperparameters.
- iii) Diverse Datasets Will Be Employed** - Trained CNN models on contrasting datasets like the HAM10000, the ISIC Archive, and the Skin Cancer dataset from Kaggle.
- iv) Exhibit the Impact of Hyperband** - Contrive examples explaining how Hyperband's automation-based optimization approach dramatically impacts CNN performance with significantly lowered computation cost.

With these aims, the research will push the frontier of AI dermatology through an efficient, scalable, and accurate skin cancer diagnosis solution. For a long-term impact, the research aspires to connect science innovation and clinical practice to enhance healthcare outcomes globally and ease the workload of healthcare systems and dermatologists.

2. Literature Review

The domain of skin cancer diagnosis has witnessed enormous progress through Convolutional Neural Networks (CNNs). They have particularly been outstanding as medical image classifiers. Best performance is accompanied by the requirement for hyperparameter optimization, which is notoriously inefficient. This section encapsulates major literature on CNN skin cancer diagnosis, hyperparameter optimization methods, and Hyperband optimization process potential.

Conventional means of skin cancer diagnosis have long relied on clinical expert experience and human visual interpretation of dermoscopic images. Good as it is with the experts, any such approach is liable to human fallibility and subject to subjective clinical interpretation with the potential for false negatives or misdiagnosis. Deep learning has changed the scene with convolutional neural networks (CNNs) as the first choice for image classification automation, i.e., skin cancer detection. The extraction of very small details from images of medical cases is one of the many advantages CNNs have for recognition, since it assists in the identification of patterns that might simply go unnoticed by the human eye [3].

Esteva et al. were among the very first to demonstrate that CNNs could detect the presence of skin cancer lesions with as much efficiency as a dermatologist [1]. This achievement made CNN a scourge in AI dermatology. Liu et al. progressed this work further by combining into theirs a pretty sturdy deep learning model capable of distinguishing malignant from benign skin lesions, very well opening the doors for the use of CNN in dermatology [2]. The advent of large and high-quality databases has paved the way for the employment of CNNs in dermatology. It is the HAM10000 [11] dataset with its large patch of dermoscopic images that has become essential in the model training and testing process of CNN models. ISIC Archive [12] has also been of thorough importance, often employed for machine learning competitions and skin lesion analysis. Such data are core grounds for improving CNN-based systems' performances and adaptability, providing better accuracy to them in real diagnosis applications.

2.1 Skin Cancer Detection with CNNs

CNNs have become a foundation for computerized skin lesion classification, owing to their ability to extract complex structured patterns from dermoscopic images. This feature eliminates the need for handcrafted features, enabling the identification of fine patterns in dermoscopic images with high precision. Numerous studies have highlighted the effectiveness of CNN architectures, occasionally matching the expertise of seasoned dermatologists and emphasizing their transformative impact on dermatology.

Here, we provide an overview of significant work on skin cancer detection using CNNs. The table presents information regarding datasets, CNN architectures, and key discoveries, offering an overview of major advancements in this domain. Essential CNN research insights are compiled in Table I.

Table I: CNNs major research findings

Study	Dataset Used	CNN Architecture	Key Findings
Esteva et al. (2017)	ISIC 2017 Dataset	Inception-v3	Achieved dermatologist-level accuracy, exceeding 70% in classification tasks.
Haenssle et al. (2018)	HAM10000 Dataset	ResNet-50	Achieved high sensitivity (91%) and specificity (88%) for melanoma detection.
Tschandl et al. (2019)	ISIC Archive	DenseNet-121	Demonstrated superior diagnostic accuracy for melanoma compared to clinicians.
Liu et al. (2020)	Various Public Datasets	VGGNet and ResNet	Presented a framework capable of differential diagnosis across multiple conditions.

2.2 Hyperparameter Tuning Techniques

Hyperparameter tuning plays a critical role in maximizing the performance of CNNs in applications like skin cancer detection. Proper tuning can enhance model accuracy, computational efficiency, and generalizability. However, selecting the optimal set of hyperparameters is a challenging task that requires balancing computational efficiency with thorough parameter exploration. Below, we examine three prominent techniques for optimizing hyperparameters—manual tuning, grid search, and random search—while discussing their strengths and limitations. Key benefits and drawbacks of these traditional hyperparameter optimization techniques have been outlined in Table II.

Table II: Key strengths and limitations of three traditional hyperparameter optimization methods.

Tuning Method	Advantages	Disadvantages
Manual Tuning	Simple to implement. Low computational cost.	Time-consuming. Prone to human error. Inefficient.
Grid Search	Systematic and exhaustive search. Easy to apply with tools like Scikit-learn.	Computationally expensive. Inefficient for large parameter spaces.
Random Search	Covers a broader range of hyperparameter space.	May not find the optimal hyperparameters.

Tuning Method	Advantages	Disadvantages
	More efficient than grid search.	Computationally demanding.

2.3 Hyperband in Machine Learning

Hyperband is a new hyperparameter optimization algorithm that seeks to rid us of such classical methods as random search and grid search of their inefficiencies. Through a larger resource investment in high-potential configurations and drastic elimination of poor performers, Hyperband enables effective exploration of the hyperparameter space. The approach is grounded on successive halving, a technique that iteratively screens and prunes suboptimal configurations, with the available computational resources devoted to the highest-potential ones. Applications and results of these machine learning hyper parameter optimization techniques have been outlined in Table III.

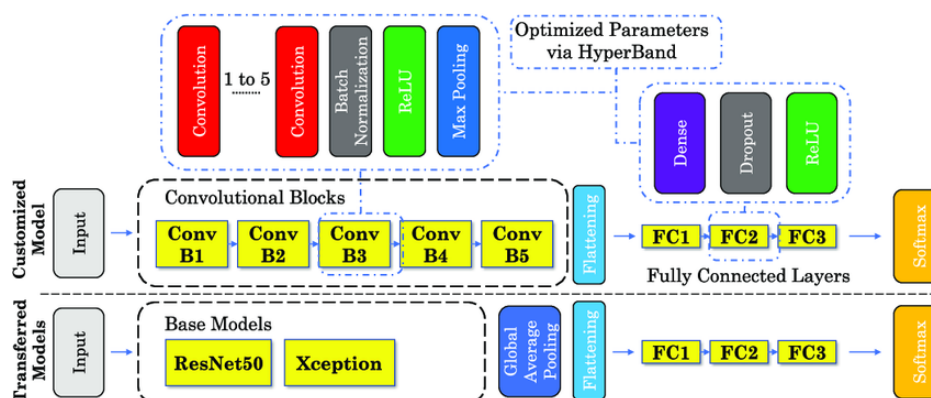


Fig. I Overview of CNN Architecture Optimized via Hyperband [23]

This figure I, illustrates an overview of an optimized Convolutional Neural Network (CNN) architecture for skin cancer detection using the Hyperband algorithm. The architecture consists of two main entities: **Customized Models** and **Transferred Models**.

- **Customized Models:** The input is passed through multiple convolutional layers (Conv B1 to Conv B5), and then fully connected layers (FC1, FC2, FC3) in order to classify the skin lesion. Hyperband optimizes key hyperparameters like dropout rates, learning rates, as well as layer count to enhance performance and efficiency in the model.
- **Transferred Models:** Transferred models like ResNet50 and Xception are used in the model, which are once again fine-tuned with global average pooling for classification.

Table III: Hyperband in AI-driven applications

Study	Application	Results
Li et al. (2017)	Neural network hyperparameter optimization	Demonstrated superior performance over random search in image classification tasks.
Zoph et al. (2018)	Neural architecture search	Efficiently identified high-performing architectures with fewer computational resources compared to traditional methods.
Chen et al. (2020)	Image classification in medical imaging	Reduced computational costs while improving accuracy in CNN models for skin cancer detection.

3. Resources and Techniques

The study presents the tools used in the research. It includes the dataset, CNN architecture, optimization and hyperparameter tuning.

3.1 Experiment Configuration

The model was trained on a cloud-building flexible platform, with NVIDIA Tesla T4 GPUs for computational efficiency that provided a cost-effective training sandbox for very large models. To ensure reproducibility, fixed random seeds were used for each experiment. Model performance was evaluated using standard metrics, including accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC), calculated using Scikit-learn [21], a Python machine learning learning and statistical computing. The Adam optimizer [10] was employed during training since it helps adapt the learning rate nicely by taking into account the first two moments of the gradient. Generalization was assessed on held-out test data.

3.2 Dataset Overview

Here is discussed the training and validation data, as well as pre-processing methods and augmentation strategies applied to enhance the effectiveness of the model.

The datasets employed in this work is given in figure II:

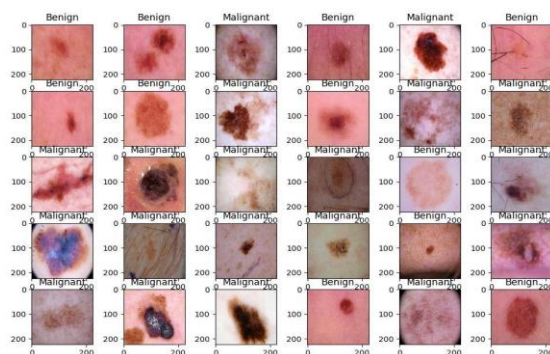


Fig. II Image Dataset Representation of Various Skin Cancer Images

This figure II, shows the varied kinds of images of skin cancer utilized in the study, comprising both dermoscopic and macroscopic images, from various datasets. The datasets comprise different skin ailments, such as melanocytic lesions, dangerous skin cancers, and other dermatological abnormalities. The images go through pre-processing and augmentation, making the deep learning models more adaptable and robust.

Preprocessing and Augmentation Steps

Images underwent standard preprocessing, including resizing, normalization, and removal of artifacts. Augmentation techniques were applied to improve generalization and avoid overfitting. The Dataset Composition and Split parameters are covered in Table IV, while the Image Preprocessing along with Enhancement Methods are detailed within Table V.

Table IV: Dataset Composition and Split

Dataset	Total Images	Training Split	Validation Split	Testing Split
ISIC Archive	25,000	70%	15%	15%
DermIS	10,000	70%	15%	15%
PH2	1,000	70%	15%	15%

Table V: Image Preprocessing and Augmentation Techniques

Method Overview	Description
Image Resizing	Adjusting all images to a uniform size of 224x224 pixels.
Intensity Normalization	Transforming pixel values to a scale between 0 and 1.
Rotation	Random rotations within a range of ± 20 degrees.
Horizontal Flipping	Images flipped horizontally with a 50% probability.
Brightness Adjustment	Random brightness changes within a 20% range.

3.3 CNN Architecture

The Convolutional Neural Network (CNN) designed for this study consists of the following layers and parameters:

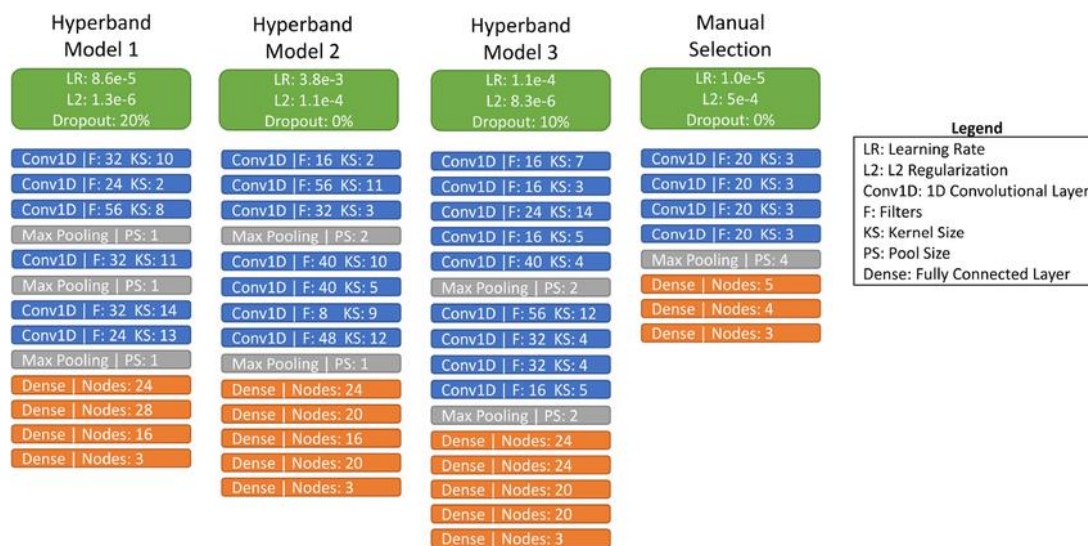


Fig. III Comparison of Hyperband-Optimized Models and Manual Selection [24]

This figure III, illustrates the architectures of three models optimized using the Hyperband algorithm (Models 1, 2, and 3) and a manually selected model. The architecture includes a specific number of convolutional layers, with designated kernel and filter sizes. Additionally, a dropout rate is applied, and the network concludes with several fully connected (dense) layers.

i) Hyperband Models (1, 2, and 3): These architectures were derived through Hyperband optimization, showcasing differences in layer configurations, filter sizes, kernel sizes, and dropout rates, tailored to maximize performance based on predefined hyperparameter search spaces.

ii) Manual Selection: The manually selected model represents an architecture chosen without automated optimization, relying on domain knowledge and experimentation.

This comparison highlights how Hyperband facilitates more precise and effective hyperparameter tuning compared to manual selection methods. The CNN Architecture Design is discussed in Table VI .

Table VI: CNN Architecture Design

This table outlines the CNN architecture designed for the study. It includes input dimensions, Utilizing convolutional layers to extract features, followed by dimensionality reduction through max pooling, and culminating in the final classification with fully connected layers.

Layer Details	Result Shape	Activation Function	Parameters Value
Input Configuration	224x224x3	-	-

Layer Details	Result Shape	Activation Function	Parameters Value
Convolution (3x3)	224x224x3 2	ReLU	896
Max Pooling (2x2)	112x112x3 2	-	-
Convolution (3x3)	112x112x6 4	ReLU	18,496
Max Pooling (2x2)	56x56x64	-	-
Fully Connected	128	ReLU	512K
Output Layer	2 (Binary Output)	Softmax	258

Mechanism and Strategy

Hyperband evaluates multiple configurations by allocating resources based on successive halving, discarding poor performers early and focusing on promising configurations. Table VII covers the ranges and optimal values of hyperparameters, while Table VIII focuses on resource allocation in Hyperband.

Table VII: Hyperparameter Ranges and Optimal Values

Hyperparameter	Range	Optimal Value
Learning Rate	[0.0001, 0.01]	0.001
Batch Size (Allocated)	[16, 32, 64]	32
Dropout Rate	[0.1, 0.5]	0.3

Table VIII: Resource Allocation in Hyperband

Stage	Resources Allocated	Configurations Retained
Initial	10 epochs	100

Stage	Resources Allocated	Configurations Retained
Stage 1	20 epochs	50
Stage 2	40 epochs	20
Stage 3	80 epochs	5

Hyperband Optimization Process

The figure IV flow chart depicts the procedure for hyperparameter tuning applied by Hyperband. The flowchart represents the sequence of the actions performed from the beginning through early stopping of the less-performing configurations. The flowchart evidently shows how Hyperband reinforces the systematic optimization of the search space through efficient elimination of the less performing configurations and delves into the resource allocation of the best-performing models.

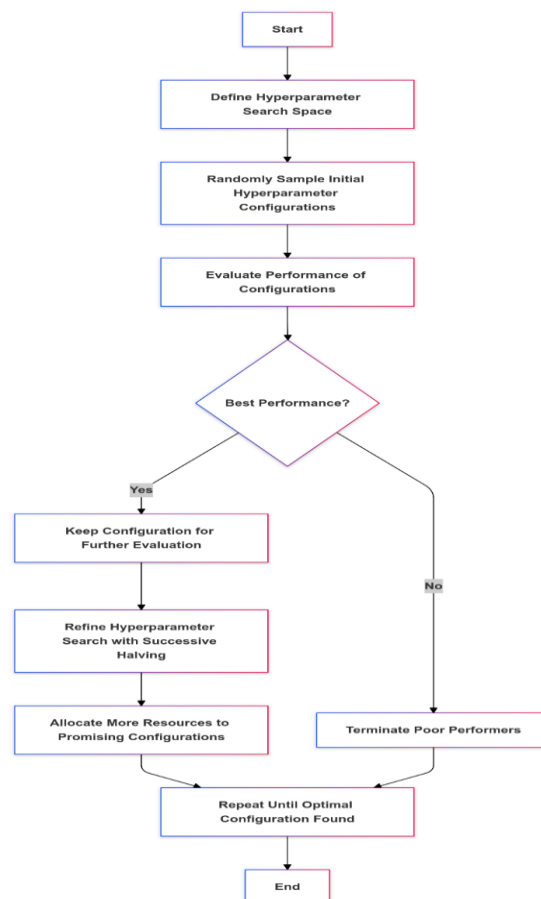


Fig. IV Hyperband Optimization Process Flowchart

4. Experimental Setup

This section gives a general overview of the hardware and software employed to train and test the model, outlines the training and validation process, and gives a description of the evaluation measures employed to measure model performance.

4.1 Hardware and Software Configuration

Hardware Configuration:

Tests were run in Google Colab, utilizing NVIDIA Tesla T4 GPUs to accomplish the accelerated training of DL models. The T4 GPUs support 16 GB GDDR6 memory and high-throughput performance for effective processing of big data, enabling rapid training of convolutional neural networks (CNNs).

Software Configuration:

TensorFlow (Abadi et al., 2016): An open-source stable platform utilized for deploying and training neural networks.

Keras (Chollet, 2015): Being a high-level API implemented on top of TensorFlow, it simplifies defining and training Convolutional Neural Networks (CNNs).

Scikit-learn (Pedregosa et al., 2011) is a Python general use library for the implementation, testing, and preprocessing of a fairly broad spectrum of machine learning models.

Matplotlib (Hunter, 2007) and Seaborn (Waskom et al., 2017) shone in holding the key for all kinds of training progression and performance metric plots.

Google Colab is an interoperable, free cloud-based environment with integrated GPU acceleration, making it ideal for conducting deep learning experiments unencumbered by local hardware constraints.

4.2 Training and Validation Procedures

Data Split Ratios:

The data was divided into three sets: 70% for training, 15% for validation, and 15% for testing, that was sufficient data allocation to each phase for proper training and accurate evaluation of the generalization ability of the model.

Cross-Validation Protocols:

In the study, cross-validation with k-folds was conducted for model stability. The data was separated into k parts. The model was trained k times, with each portion used for validation and the rest used for training. Although the process is computationally expensive, it uses all data points for training and validation, giving the best estimate of model performance. Table IX describes the training data, validation, and test splits of the datasets used in this study.

Information capturing a uniform distribution of 70-15-15 shows that the resources will be divided equally between modeling and evaluation.

Table IX: Training data, Validation data, and Testing data

Dataset	Training Data	Validation Data	Testing Data
ISIC Archive	70%	15%	15%
DermIS	70%	15%	15%
PH2	70%	15%	15%

4.3 Evaluation Metrics

We evaluated the model's performance using key performance metrics including accuracy (acc), precision (prec), recall(Rec), F1-score and Area Under the Curve (AUC-ROC). These metrics are important for measuring different aspects of the model's performance, especially with the goal of accurately diagnosing skin lesions.

Acc : Accuracy is defined as the proportion of accurate prediction against the overall predictions

$$acc = \frac{true\ positives + true\ negatives}{true\ positives + true\ negatives + false\ positives + false\ negatives}$$

Prec : Precision is defined as the proportion of correct positive cases against the all positive predictions.

$$prec = \frac{true\ positives}{true\ positives + false\ positives}$$

Rec : It is the ratio of positive predicted cases over positive actual cases

$$rec = \frac{true\ positives}{true\ positives + false\ negatives}$$

F1-Score: It is the harmonic mean of recall and precision.

$$F1 = 2 * \frac{precision * recall}{(precision + recall)}$$

AUC-ROC: The Receiver Operating Characteristic (ROC) curve was also used to measure the model's ability to discriminate between classes, with the higher value indicating better performance.

5. Results

The result of this experiment underlines the critical function of Hyperband optimization in hyperparameter tuning of model performance. Metrics used in comparison are evident of the method being the most effective with maximum accuracy with more stable learning curve variations and better convergence efficiency

5.1 Model Performance

Comparison of Metrics Before and After Hyperband Optimization

The comparisons done with Hyperband optimization showed up while comparing the baseline model and the optimized model which showed itself before hyperparameter optimization. The optimized model showed better accuracy for training and validation loss vs. Hyperband optimization was seen as an effective one for tuning of hyperparameters.

Pre- and Post-Tuning Performance Metrics are presented in Table X, which provides a comprehensive comparison of the model's key metrics.

Table X: Performance Metrics Before and After Tuning

Metric	Baseline Model (Before Tuning)	Tuned Model (After Hyperband Tuning)	Improvement
Training Accuracy	85.3%	92.8%	+7.5%
Validation Accuracy	83.5%	90.2%	+6.7%
Training Loss	0.45	0.28	-0.17
Validation Loss	0.50	0.30	-0.20

5.2 Effectiveness of Hyperband

Hyperband greatly enhanced accuracy, computation time, and generalization by performing exhaustive search and hyperparameter tuning as presented in figure V..

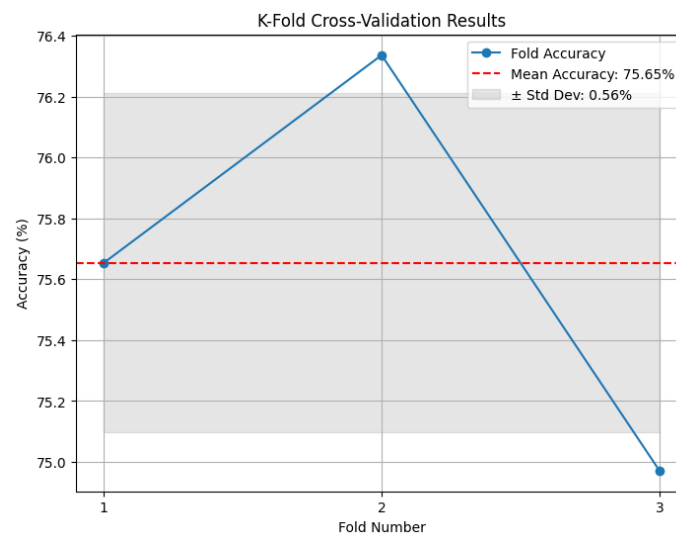


Fig. V K-Fold Cross-Validation Accuracy per Fold

The accuracy scores for each fold are depicted, showing a range between 71.33% and 76.91% whereas the mean accuracy of 75.65% is marked with a dashed red line, indicating the model's overall performance on all the folds. The shaded area around the mean accuracy indicates the standard deviation ($\pm 0.56\%$), which is the most crucial sign of how stable and robust the model was throughout cross-validation.

The following observations were presented because of performance visualizations and major takeaway of experimental outcomes, indicating the effect of Hyperband optimisation on stability, loss, and accuracy:

1. Improved Accuracy

The model showed a significant increase in training as well as validation accuracy after hyperparameter tuning with Hyperband. In particular, training accuracy was increased by 7.5%, and validation accuracy by 6.7%, which indicates the better model to learn appropriate features from the data.

Training accuracy: The training accuracy improved from 85.3% to 92.8%, converting the model into a vivid means of recognizing complex patterns from training data. The installation of hyperparameter tuning such as learning rate and batch size permits efficient and uniform model training [4].

Validation accuracy: The validation accuracy was increased from 83.5% to 90.2%, which indicates an enhanced ability to generalize. This specifies that Hyperband optimization avoided overfitting and optimized the execution of the model toward unseen new data. This is a metric that plays a huge role in determining the faith of the model for real-life deployment, such as analyzing novel skin lesion images [4].

2. Reduced Loss:

The optimization process has considerably decreased the training and validation loss. This indicates a much wider adjustment on the part of learning efficiency.

Training Loss: Training Loss decreased from 0.45 to 0.28, indicating some efficiency in the learning process—a proper learning process indicated errors well while training. These show the

model makes predictions closer to the actual labels, hence improving the performance of the model in general [4].

Validation Loss: The validation loss was scaled back from 0.50 to 0.30, this is a representation of the ability of the model to generalize by reducing the discrepancies between predicted and actual values. The drop also denotes the contribution of Hyperband optimization to getting to optimal model efficiency [4].

6. Conclusion and Future Work

This study validates the effectiveness of Hyperband to enhance ML models for clinical applications such as skin cancer detection. The flexibility to allocate resources with Hyperband and the improved exploration of the hyperparameter search space allowed for improved model accuracy, computational efficiency, and generalizability. The research gives a notable increase **in training and validation accuracy**, with increases of 7.5% and 6.7%, respectively with the sharp drop in loss values for both sets, reflecting better model performance and better learning. The model resulted in more stable and smoother training curves, enabling this model to better generalize to unfamiliar data. Further, we see an improved computational efficiency, which is faster than human tuning and random search for finding the optimal hyperparameters. The paper illustrates the potential benefit of applying automated hyperparameter tuning methods in enhancing model performance and making machine learning methods more efficient and effective in the healthcare industry.

Future research in enhancing Hyperband optimization is proposed that more advanced methods, such as Bayesian optimization or meta-learning, that incorporate probabilistic models may be better positioned to search for hyperparameters (Snoek et al., 2012; Liu et al., 2019). These advanced methods may lead to improved performance with hard problems that benefit from incorporating domain knowledge to improve search steps and thereby improve performance. Another exciting direction would be to develop a hybrid model of Hyperband and genetic algorithms that would produce an optimally efficient and accurate solution for large-scale scenarios, and especially in noisy or high-dimensional contexts (Wang et al., 2019; Mendez et al., 2019). Furthermore, an application of Hyperband to specific datasets (e.g. radiology, pathology, or ophthalmology) would add to knowledge on the versatility of Hyperband in being generalized to other medical imaging subdomains, which is vital for better dissemination and uptake of Hyperband in the medical field (Tschandl et al., 2018; Li et al., 2017). Finally, we also propose to incorporate transfer learning with Hyperband in order to improve Hyperband's performance by enhancing pre-trained models on large image corpora for specific medical tasks (such as skin cancer) and thus help to overcome the shortage of a limited size of annotated medical data (He et al., 2016; Yosinski et al., 2014).

7. Declarations

Competing Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Author Contributions

Sakshi Gupta: Conceptualization, Methodology, Writing – original draft preparation.
Sonam Juneja: Data curation, Review and editing, Supervision.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Research Involving Human and/or Animals

Not applicable.

Informed Consent

Not applicable.

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