Hyperparameter Optimization in CNN: A Review

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***Abstract*—Hyperparameter optimization is an important issue in convolutional neural networks (CNNs), which is an appropriate deep learning network for image classification. Several classical and metaheuristic algorithms are often employed to optimize hyperparameters. In the present paper, different algorithms are compared by using various evaluation measures. The literature reveals that genetic algorithms (GA) and PSO or particle swarm optimization are the most effective algorithms for hyperparameter optimization used in a variety of domains including disease diagnosis; face detection, and handwritten character recognition. Further, it is concluded that optimized CNNs, are essential to the early detection of a variety of diseases, which can assist physicians and clinicians in saving lives by providing accurate and timely predictions.**

Keywords— particle swarm optimization; hyperparameter optimization; convolutional neural network; genetic algorithm.

I. INTRODUCTION

Disease prediction in the early stages is a challenging task, and distinguishing one disease from another through differential diagnosis takes a significant amount of time. It can be made easier, earlier, more timely, and more accurate by utilizing techniques of machine learning [1]. Artificial neural networks (ANNs) [2], usually referred to as neural networks are among the prominent ML technique for disease prediction. However, when used on image data, their performance could suffer. Convolutional neural networks, or CNNs, are made to classify images, and optimizing hyperparameters is crucial to getting the best CNN performance. Finding the optimal values for hyperparameters is a challenging task, as their impact on the model's execution can be complex and highly dependent on the specific problem and dataset. Suboptimal models with poor performance often result from relying solely on intuition or employing trial-and-error approaches. Therefore, systematic and efficient optimization techniques are required to find the optimal values for hyperparameters. Several approaches for hyperparameter optimization are commonly used, such as manual search, random search and grid search. In recent years, more advanced techniques such as gradient-based optimization; Bayesian optimization; evolutionary algorithms; and grey wolf optimization methods have gained popularity. These methods rely on statistical modeling, probabilistic reasoning, and optimization algorithms to efficiently guide the search process. Hyperparameter optimization is crucial for facial recognition, climate change evaluation, advertising, and early diagnosis of diseases like cancer diagnosis [3], heart disease prediction [4], diabetes classification [5], rare disease diagnosis [6], and more. It is important to note that while hyperparameter optimization can enhance the performance of machine learning models in healthcare applications, it should be complemented with proper data collection, preprocessing, and domain expertise to ensure accurate and reliable disease diagnosis or prediction. The main applications of hyperparameter optimization include enhancing model performance, mitigating overfitting, expediting model training, optimizing resource utilization, achieving model generalization across different datasets, and exploring model architecture. Inspite of its significant potential for improving model performance, hyperparameter optimization also presents various challenges. These challenges encompass time and computational resource requirements, the curse of dimensionality, lack of generalization, the non-convex nature of the optimization landscape, interdependencies between hyperparameters, limited domain knowledge, and issues related to reproducibility and consistency. Therefore, a comprehensive and detailed literature review can provide updated knowledge, the latest insights, applications, and a comprehensive understanding of the field of hyperparameter optimization, including the algorithms employed in this context.

The paper's structure is set out as follows: Section II provides information on the CNN layers; hyperparameter optimization is described in Section III, Related work presented by Section IV, Section V discusses evaluation methods, and Section VI provides a conclusion.

II Convolutional Neural Networks

The CNN is the most used image classification technique and the best answer for issues requiring picture categorization. "The convolutional layer, pooling layer, and fully connected layer" are three layers of CNN [7]. A brief description of each layer including its function has been shown below.

A. Convolutional Layer

The most important part of the CNN model is the convolutional layer, which is made up of many convolutional filters that carry out convolutional operations. These filters are small and are used for feature detection and extraction, such as sharpening, blurring, and so on. These filters are called kernels. An output feature map is created when the kernel convolves the input picture. The feature map's size is determined by three parameters: zero-padding, stride, and depth. Depth is the number of filters used. Stride is defined as the distance between two consecutive positions of the kernel. In the padding, zeros are added on all sides of the image to apply filters to bordering elements [8][9].

B. Pooling Layer

Subsampling layer is the second name for the pooling layer. In this layer, the dimensions of feature maps are reduced, and the most important information stays. Two Pooling techniques are maximum pooling and average pooling. In average and maximum pooling, the average value and maximum value are selected within the pooling window, respectively [10].

C. Fully Connected Layer

CNN model's last layer is full connected. The fully connected layer and ANN have the same structure. It takes input from the previous layer, and the final image is the output of the output layer based on the classifier [11].

III Hyperparameter Optimization

Adding layers to the CNN model made it work better, but as the number of layers increased, the model's performance started to deteriorate. Thus, optimizing hyperparameters is a more effective way to enhance CNNs. In machine learning, model parameters, and hyperparameters are two types of parameters. The parameters, whose values are learned from data and used within the model are called model parameters. Coefficients, weights, and support vectors are model parameters in linear regression, ANN, and support vector machines, respectively. The parameters whose values are set before starting the model training process are called hyperparameters [12][13]. It plays a very important role in deciding the accuracy and convergence of the CNN models and that depends on the datasets for which the CNN model is used. The network parameters updated the by learning algorithm many times by the training dataset are determined by the number of epochs. Therefore, tuning the hyperparameter gives the most accurate results. "Hyperparameter optimization is the process of figuring out the best set of hyperparameter values to obtain the best results on the data in a reasonable amount of time". Hyperparameter that decides the structure of the network and the hyperparameter that determines the network trained are two types of hyperpaarmeters.

Hyperparameter that decides the structure of the network includes Padding, Kernel size, Hidden Layer, Stride, Activation Functions, and Kernel type [14].

- Kernel: "Features are extracted from the images by using a filter called kernel".
- Stride: "Stride is defined as the distance between two consecutive kernel positions".
- Padding: "In the padding, zeros are added on all the sides of the image".
- Hidden Layer: "Hidden layers are those that are located between the input and output layers".
- Activation Function: "The activation function is the building block of neural networks that decides which signal should pass from one neuron to another [15]. There are linear and non-linear activation functions, which are categorized into ELU (Exponential Linear Units), ReLu (Rectified Linear Units), Sigmoid Function, Hyperbolic Tangents, Step Function, and linear activation function" [16].

Hyperparameter that determines the network trained such as; momentum, batch size, learning rate, and epochs.

- Learning rate: "It regulates at the end of each batch on the update of the weight".
- Momentum: "It modifies the value such that the most recent weight update is influenced by the prior one.".
- Epochs: "When training, the network is subjected to iterations of the whole training dataset."
- Batch size: "The quantity of patterns displayed to the network prior to the updating of the weights".

A. Algorithms for Hyperparameter Optimization

Grid search

It is considered one of the most important methods for hyperparameter optimization. It involves trying all possible values of hyperparameters and is characterized by its trivial parallelization. The grid search method is particularly beneficial when dealing with a small amount of data. However, when dealing with a lot of data, it takes a lot of time. [17].

Random Search

Random search is another method utilized for hyperparameter optimization. In this method, random combinations of hyperparameters are tested, and the best combination is selected. Random search is advantageous when working with a lot of data as it takes less time as compared to grid search. However, it does not utilize previous experience to select the next set of hyperparameters, making it a time-consuming process [18].

Bayesian Optimization

Bayesian optimization, also called Model-Based optimization, is based on Bayes theorem which is based on conditional probability. It is better than grid and random search in two ways, the first is that it learns from its previous iterations, and the second is the posterior probability. It is applicable despite the fact that the objective function is stochastic or discrete, or convex or nonconvex [18]. It is the most efficient way of finding the optimum hyperparameter.

Genetic algorithms

Genetic algorithms (GA) are metaheuristic algorithms inspired by biological theories, proposed by John Holland. They find the optimal solution to difficult problems by competing individuals, and selecting the fittest for survival. In this, each hyperparameter is represented by a chromosome that has a corresponding fitness value and on this basis optimal solution to the problem is selected [18]. There are three genetic operators viz. crossover, selection, and mutation. These operators are used to develop gradually from the best individuals. A population is created by randomly selecting individuals according to their fitness values. This process is continued until the termination is reached and the optimal solution is determined [19].

Particle Swarm Optimization (PSO)

The PSO algorithm draws inspiration from the swarming behavior of birds in social situations. It needs only an objective function and is not dependent on the gradient or any differential form of the objective. Each particle in PSO has the position and velocity of the best particle to date, and the collection of particles is referred to as a swarm. Each particle's performance is calculated on the basis of velocity and position. This calculated information is used for the next iteration. This iterative process continues until the desired result is obtained [18].

IV Related Work

A "random grid coarse-to-fine search optimization approach," which integrates grid search, random search, and a coarse-to-fine approach, was employed by A. Nurhopipah and N.A. Larasati (2021) in their study methodology. The proposed model was implemented on low-quality face detection images. The authors used the SELU activation function which gives the best performance. Hyperparameters were optimized by applying the grid coarse-to-fine method and grid search. This gives an accuracy of 89.56 %. Denoising wavelet techniques were used in this study that improved the image quality and increased the accuracy value to 92.89%.The activation function was optimized using exhausted-random-search and increased 97.11% accuracy. By employing this approach to other hyperparameters, 97.56% accuracy was achieved [17].

Research on identifying chest X-ray pictures of COVID-19 using a GWO and Whale Optimization + BAT method, ResNet 50-Error Correcting Output Code (ECOC) model for optimizing CNN model, was proposed by S. Pathan et al. in 2021. For datasets 1 and 2, the classification accuracy of pictures into normal, COVID-19, and pneumonia cases was found to be 98.8% and 96%, respectively [20].

The EVO approach to detecting cancer cell existence was undertaken by M. Alnabhan et al. (2022). Hyperparametres were optimized using the EVO approach. This model was compared with ELM, MLP, CNN, and DNN. The model was evaluated on the basis of two datasets ("Glioma and Brain MRI image datasets"). CNN model after hyperparameter optimization performed better using the EVO technique. Accuracy (93%) and precision (95%) were obtained [21].

In their research, T. Goel et al. (2021) employed OptCoNet, for the automatic diagnosis of normal, pneumonia, and COVID-19 images. GWO algorithm was used to optimize the hyperparameters. This CNN model provided an accuracy of 97.78% [22].

A.E. Minarno et al. study from 2021 used a CNN (convolutional neural network) with hyperparameter tuning to classify brain tumors. CNN models with different combinations of hyperparameters is used to classify four classes of brain tumor (meningioma, pituitary, glioma, no tumor). The three models were implemented. In the first model, accuracy was 86%. In the second model, accuracy was 91%. In the third model, accuracy was 96%. The third model performed better. Hyperparameter Tuning improved performance [23].

M. Loey et al. (2022) used a CNN model for classifying X-ray images based on Bayesian optimization. Bayesian optimizer modifies the CNN hyperparameters. The dataset consisted of 10,848 images, including 3616 images of pneumonia, 3616 images of covid-19, 3616 normal images. The Bayesian optimization gave an optimal architecture with 96% accuracy [24].

In a study conducted by F.M. Talaat et al. (2022), a new reinforcement learning (RL) based algorithm was proposed for optimizing the hyperparameters of CNNs. CNN optimized by RL-based optimization algorithm (ROA) gave accuracy of 98.97% when working with the MNIST dataset. Similarly, when the CIFAR-10 dataset was used, CNN optimized by ROA gave an accuracy of 73.40% [25].

In a paper by F. Golnoori et al. (2023), three metaheuristic optimization algorithms, namely PSO, GA, and DE, were utilized. The focus of the study was on early diagnosis of melanoma. The author aimed to enhance the performance by optimizing the hyperparameters using these algorithms while employing a KNN classifier. Two datasets, namely ISIC 2017 and ISIC 2018, were utilized in the experiments. The achieved accuracy was 81.6% on ISIC 2017 and 90.1% on ISIC 2018 [26].

In this study, the classification of crop pests was conducted by E. Ayan (2023). The genetic algorithm was utilized for hyperparameter optimization of CNN models. The three CNN models, namely DenseNet121, MobileNetV2, and InceptionResNetV2, were employed at different scales. 10 classes of Deng's dataset, 40 classes of Xie2's dataset D0, and 102 classes Wu's dataset IP102 were the three datasets used.

An accuracy of 99.89% was achieved on the D0 datasets, while the accuracy on Deng's dataset was 97.58%. Moreover, the performance on the IP102 dataset closely matched the literature, reaching 71.84% [27].

In the paper authored by S. Kilicarslan (2022), a hybrid model was proposed for predicting cardiovascular diseases. PSO, CSO, and a combination of PSO and GWO algorithms were employed for hyperparameter optimization. The VGG-16 model was utilized, and the MNIST dataset was employed for experimentation. The finest outcome was attained by using the combination of PSO and GWO algorithms. An accuracy of 92.38% was obtained by using PSO, while CSO achieved an accuracy of 92.22%. The proposed hybrid of PSO and GWO outperformed both, achieving an accuracy of 93.38% [28].

In a paper by E. Michael et al. (2022), the classification of malignant and benign tumors was done by using five machine-learning classifiers. The experiment's findings illustrated Bayesian optimization using a tree-structured Parzen estimator based on machine learning classifiers for 10-fold cross-validation. The LightGBM classifier outperformed the other four classifiers, with an accuracy of 99.86% [29]. The data related to the comparative analysis of different algorithms and their accuracy is given in Table I.

V Evaluation Measures

There are several evaluation measures used to check the model's performance, and these are specificity, F1 score, accuracy, sensitivity, precision, and recall. Four fundamental components are required for these measurements: true positive (TP), false positive (FP), false negative (FN), and true negative (TN). The terms "true positive" and "true negative" refer to correctly labeled positive and negative cases, respectively, whereas "false positive" and "false negative" refer to mistakenly labeled positive and negative examples, respectively [30][31][32][33].

- Specificity = — (N=FP+TN) (1)
- Accuracy = —— (2)
- Sensitivity = — (P=TP+FN) (3)
- Precision= —— (4)
- F_1 = —————— (5)
- Recall= —— (6)

TABLE I Comparative Analysis Of Different Algorithms And Their Accuracy

No.	Author	Year	Algorithms	Class	Accuracy	Precision	Sensitivity	Specificity	Recall
1.	A. Nurhopipah, and N.A. Larasati, [14]	2021	Random, Grid, coarse-to-fine search	Face detection images	97.56%	-	-	-	-
2.	S. Pathan et al. [17]	2021	Whale optimization + BAT algorithm, Grey Wolf Optimizer (GWO)	Dataset1 Dataset2	98.8%, 95%	98% 94%	1 95%	99% 99%	-
3.	M. Alnabhan et al. [18]	2022	Egyptain Vulture Optimization technique	Glioma, Meningioma No tumour Pituitary	98.47% 98.47% 99.23% 98.73%	96.91% 97.35% 99.01% 97.22%	- - - -	98.98% 98.92% 99.65% 99.38%	96.91% 97.35% 98.04% 95.89 %
5.	T. Goel et al. [19]	2021	Grey Wolf Optimizer (GWO)	COVID-19, Normal Pneumonia	97.78 %	92.88%	97.75%	96.25%	-
6.	A.E. Minarno et al. [20]	2021	The third model outperformed the previous two.	Model 1 Model 2 Model 3	86% 91% 96%	87% 91% 96%	- - -	- - -	86% 91% 96%
7.	M. Loey et al. [21]	2021	Bayesian optimization	COVID-19, Normal Pneumonia	96%	-	-	-	-
8.	F.M. Talaat et al. [22]	2022	Q-learning RL-based optimization (ROA)	MNISTdataset CIFAR-10 dataset	98.97% 73.40%	-	-	-	-
10.	F. Golnoori et al. [23]	2023	GA,DE,PSO	ISIC 2018 ISIC 2017	90.1% , 81.6%,	89.8% 81.18%	-	-	90% 81.67%
11.	E. Ayan et al. [24]	2023	Genetic Algorithm	D0 datasets Deng's dataset IP102 dataset	99.89%, 97.58%, 71.84%	99.82 % 97.79 % 65.85%	-	-	99.91% 97.79% 63.22%
12.	S. Kilicarslan et al. [25]	2022	Particle swarm optimization, Cat Swarm optimization	MNIST dataset	93.38%	94.25%	-	-	94.21%

13.	E.Michael et al.	2022	Bayesian optimization using a tree-structured Parzen estimator	Malignant tumors Benign tumors	99.86%.	100.0%			99.60%

VI CONCLUSION

The present work provides an exhaustive overview of the hyperparameter optimization of CNNs. In various applications like medical diagnosis, agriculture, food safety, etc. accurate and fast prediction is the prime concern. Utilizing the advanced algorithms for hyperparameter optimization improves both the issues. The present review article reveals an important outcome as Genetic Algorithm, Egyptian Vulture Optimization, and Whale Optimization outperformed other contemporary optimization techniques, but in areas like medical diagnosis accuracy is always a crucial issue. Therefore, by utilizing advanced metaheuristics for hyperparameter optimization, there is still room for advancement in CNNs. These improvements make medical facilities more accurate, accessible, and effective for society.

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