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HYPERPARAMETER TUNING OF CNN USING BAYESIAN OPTIMIZATION ON GASTRIC CANCER HISTOPATHOLOGICAL IMAGES

Radhika Shetty D S[1*], Antony P J[2]

[1]Research Scholar, Department of Computer Science & Engineering, A.J. Institute of Engineering and Technology, Affiliated to Visvesvaraya Technological University, Belagavi, Mangalore, Karnataka, India

[2]Vice Principal & Head, Department of Computer Science & Engineering, A.J. Institute of Engineering and Technology, Affiliated to Visvesvaraya Technological University, Belagavi, Mangalore, India.

***Corresponding Email id:** ss.radhika@gmail.com

Abstract

Hyperparameter tuning is an essential procedure for improving the precision and effectiveness of Convolutional Neural Networks (CNNs), especially in the examination of medical images. This paper examines the optimization of CNN hyperparameters by Bayesian methods and Keras Tuner, applied to a dataset of histopathology images of gastric cancer. We modified critical hyperparameters such as the learning rate, batch size, number of filters, kernel size, dropout rate, and optimizer type to enhance the model's ability to identify malignant traits. We employed Bayesian optimization to efficiently navigate the hyperparameter space, significantly reducing the number of iterations required in comparison to exhaustive search techniques. The experimental results demonstrated that the model excelled in classification, converged more rapidly, and exhibited superior generalization. The study emphasizes the effectiveness of Bayesian optimization in CNN applications focused on medical imaging and offers a practical approach for hyperparameter tuning using Keras tools.

1. Introduction

Convolutional Neural Networks, often known as CNNs, have brought about a revolution in the field of computer vision by providing state-of-the-art performance in a variety of image-related tasks. These tasks include segmentation, object detection, and classification. In the past few years, CNNs have demonstrated a great deal of promise in the field of medicine, particularly when it comes to the analysis of histological pictures[1]. In this field, accurate categorization is of utmost importance for the early diagnosis and prognosis of diseases. However, the performance of a CNN is heavily dependent on its hyperparameters, which are the settings that affect the learning process yet remain constant throughout the training phase. The learning rate, batch size, number of filters, kernel size, activation function, dropout rate, and kind of optimizer are some examples of characteristics that can be considered. It is necessary to select the appropriate combination of these hyperparameters in order to achieve high levels of model accuracy and increased generalization capabilities.

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1.1. The Challenge of Hyperparameter Tuning

Hyperparameter tuning is inherently a black-box optimization problem—there is no closed-form solution to determine which set of hyperparameters will yield the best model performance for a given dataset. Traditionally, researchers have relied on manual tuning, which is time-consuming, subjective, and prone to suboptimal results. To overcome these limitations, automated tuning strategies have been developed.

Grid Search is the simplest method as it examines every possible combination of predetermined hyperparameter values. Grid search is straightforward and comprehensive; nevertheless, it rapidly becomes expensive and inefficient as the dimensionality of the hyperparameter field increases [1]. Bergstra and Bengio proposed Random Search as a solution to this issue by randomly selecting hyperparameter combinations[2]. Studies demonstrate that random search can outperform grid search by covering a broader segment of the search space with fewer iterations, especially when a small number of hyperparameters significantly affect model performance.
Both grid and random search exhibit a significant flaw: they treat each trial independently and fail to leverage the outcomes of previous evaluations to inform subsequent searches. Due to their failure to learn from previous evaluations, they inadequately explore the hyperparameter space.

1.2. Bayesian Optimization: A Smarter Approach

Bayesian optimization addresses this limitation by modelling the objective function (e.g., validation accuracy or loss) as a probabilistic function and updating this model based on previous trials. Using methods such as Gaussian Processes (GPs) or Tree-structured Parzen Estimators (TPE), Bayesian optimization identifies the most promising hyperparameter configurations to evaluate next by balancing exploration (trying new areas of the search space) and exploitation (focusing on areas known to perform well) [3]. This makes it significantly more sample-efficient than traditional methods.

In the context of deep learning, Bayesian optimization has gained popularity due to its ability to find high-performing configurations with fewer model evaluations, thereby saving time and computational resources. Tools like Keras Tuner provide a user-friendly implementation of Bayesian optimization and are compatible with TensorFlow/Keras models. Keras Tuner allows practitioners to define a search space and automatically selects optimal parameters through an intelligent, iterative process.

1.3. Application to Gastric Cancer Histopathological Image Classification

We use Keras Tuner to fine-tune a CNN model for the categorization of histological pictures of stomach cancer in this study. Gastric cancer continues to be a predominant cause of cancer-related mortality globally. For survival rates to go up, early detection is very important. In clinical settings, histopathology-based diagnosis is the best way to do this. Automating this diagnostic procedure with deep learning can help pathologists and make diagnoses more accurate, especially in places where resources are limited.

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Our work involves constructing a custom CNN architecture and tuning its hyperparameters using Keras Tuner's Bayesian optimization strategy. The key hyperparameters considered include learning rate, batch size, number of filters in convolutional layers, kernel size, dropout rate, and optimizer selection. The tuning process is evaluated based on model accuracy, training time, and generalization on unseen test data.

1.4. Contributions of this Study

This paper makes the following key contributions:

- Provides a comparative analysis of different hyperparameter tuning methods with a focus on Bayesian optimization.
- Implements Bayesian optimization using Keras Tuner for tuning CNNs applied to gastric cancer histopathology images.
- Demonstrates the efficiency of Bayesian tuning in achieving improved model performance with fewer evaluations.
- Offers a reproducible workflow that can be extended to other medical image classification tasks.

2. Literature Review

Hyperparameter optimization (HPO) is crucial for enhancing the performance of deep learning models, especially CNNs, where decisions regarding learning rate, optimizer, architecture, and regularization profoundly affect outcomes. Grid search and random search are two common approaches that have been around for a long time, but they don't work well in high-dimensional areas since they are slow and don't scale well.

Random search, as shown by Bergstra and Bengio (2012)[1], often outperforms grid search by exploring the hyperparameter space more efficiently when only a few parameters matter . Metaheuristic algorithms such as genetic algorithms, particle swarm optimization (PSO), and ant colony optimization have been applied to CNN tuning in medical imaging tasks. For instance, a hybrid genetic-Bayesian approach was used to optimize deep neural network parameters . Another study optimized CNN hyperparameters through PSO for breast cancer classification using mammograms, achieving high accuracy .

Bayesian Optimization (BO) frames HPO as a sequential model-based optimization problem, typically using Gaussian Processes (GPs) or Tree-structured Parzen Estimators (TPE) to build surrogate models and acquire new hyperparameter trials via acquisition functions like Expected Improvement or UCB . Snoek et al. (2012)[3] demonstrated BO's effectiveness in tuning ML algorithms including CNNs, outperforming manual tuning and naive search . Bischl et al. (2021)[4] provided a comprehensive overview including BO, Hyperband, racing methods, and best practices in HPO . Onorato (2024)[5] applied BO to CNN hyperparameter tuning, showing rapid convergence and reduced evaluation counts .

To further reduce computational costs, hybrid methods combining BO with Hyperband (BOHB) have been proposed. Falkner et al. (2018)[6] introduced BOHB, which integrates

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BO's guidance with Hyperband's early stopping, achieving state-of-the-art tuning performance on CNNs . Hamad et al. (2024)[7] reviewed metaheuristic methods including BO and various evolutionary strategies for CNN tuning in medical imaging . Other tools like Optuna support TPE, CMA-ES, and pruning-based multi-fidelity optimization and have seen applied success in biomedical CNN tasks .

In medical imaging, Bayesian optimization has improved CNN tuning efficiency and accuracy across various domains. For brain metastasis classification from MRI, BO guided architecture and hyperparameter selection, outperforming expert radiologists in AUC and generalization . A study focused on diabetic maculopathy classification using OCT/fundus images similarly used BO to refine CNN performance efficiently . A broader survey of disease detection via CNNs highlights numerous instances of Bayesian-based tuning in leukemia detection, COVID-19 CT/X-ray classification, and more .

Shahriari et al. (2015) reviewed Bayesian optimization fundamentals, demonstrating its ability to "remove the human from the loop" in HPO . Bischl et al. (2021)[4] analyzed practical challenges and provided guidance on evaluation metrics, pipeline integration, and parallelization . Community discussions emphasize BO's strengths but note sensitivity to noise assumptions and continuous hyperparameter domains . Reddit practitioners also highlight hybrid methods like BOHB and propose using smaller proxy tasks for tuning prior to full-scale modelling . Table 1 summarizes key literature on CNN hyperparameter tuning across methods:

Table 1: Literature review summary

Study / Method	Approach	Domain	Key Outcome
Bergstra & Bengio (2012)[1]	Random Search	General	Efficient vs grid search
Snoek et al. (2012)[3]	Bayesian Optimization	ML algorithms incl. CNN	Expert-level tuning performance
Onorato (2024)[5]	BO with BotTorch	CNN for image classification	Reduced trials, high accuracy
Falkner et al. (2018)[6]	BOHB	CNN tuning	Fast convergence with resource control
Hamad et al. (2024)[7]	Metaheuristic BO/Evolutionary	Medical imaging	Survey of optimization methods
Atteia et al. (2022)[8]	BO-optimized CNN (medical)	Retinopathy, leukemia	Improved performance via BO
Oliveira et al. (2021)[9]	BO for brain MRI classification	Medical imaging	Outperformed expert radiologists

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Study / Method	Approach	Domain	Key Outcome
Inik et al. (2025)[10]	Hybrid PSO + ABC	MNIST RD, MNIST BN, MNIST BI, and MNIST RD+BI	Joint architecture + parameter optimization

This research demonstrates that Bayesian optimization—particularly when integrated with multi-fidelity approaches such as BOHB or efficient frameworks like Keras Tuner—yields substantial improvements in performance, efficiency, and resource utilization in CNN hyperparameter tuning. These characteristics make BO a strong candidate for our use in classifying histological images of stomach cancer.

3.Proposed Method

When you tune hyperparameters in deep learning, you have to choose from a lot of different alternatives. But not all hyperparameters improve model performance equally, and tweaking too many at once might make the calculation much harder without making any real improvements. In this study, we selected four critical hyperparameters based on their well-documented influence on CNN performance, especially in the context of medical image classification:

- **Number of Convolutional Layers**: This directly impacts the model's depth and capacity to extract hierarchical features. A deeper model can capture more abstract representations, which is especially useful in complex image domains like histopathology. Tuning this allows us to balance underfitting (too shallow) and overfitting (too deep).

- **Learning Rate**: This is perhaps the most sensitive hyperparameter in any deep learning model. It controls how quickly the model updates its weights and can greatly affect convergence speed and stability. Incorrect values can lead to divergence or excessively slow learning.

- **Dropout Rate**: Dropout is a regularization technique that prevents overfitting, especially important when dealing with limited medical datasets. Tuning the dropout rate helps control the trade-off between model complexity and generalization.

- **Optimizer Selection**: The choice of optimizer (e.g., Adam, SGD, RMSprop) affects the gradient descent behavior and model convergence. Different optimizers handle learning rate schedules and momentum differently, which can impact training dynamics and final accuracy.

These parameters were selected because they are:

- Highly influential on model behavior
- Computationally manageable for tuning with Bayesian optimization
- Generalizable across different CNN architectures

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3.1 Other Common Hyperparameters (Not Tuned in This Study)

Several other hyperparameters exist but were either fixed or not included in the search space for specific reasons:

Table 2: Hyper Parameters

Hyperparameter	Reason for Not Tuning
Batch Size	Fixed to reduce variability across trials and because tuning it often provides marginal gains relative to cost.
Activation Function	ReLU is the standard default for CNNs and performs robustly in most image classification tasks.
Kernel Size / Stride	Usually set to 3×3 and 1 respectively in VGG-style architectures. These are architectural choices rather than tuning priorities.
Weight Initialization	Keras provides reliable defaults (e.g., He or Glorot initialization), and their impact is generally minor compared to learning rate and optimizer.
Pooling Type (Max/Average)	Max pooling is commonly used in CNNs; varying it has negligible performance effect.
Number of Dense Units	Often fixed relative to the number of classes or size of feature maps before flattening.
Epochs	Early stopping is used; tuning epochs may not be as critical as tuning learning rate and dropout.

3.2 Strategic Considerations

Computational Constraints: Changing a lot of hyperparameters makes the search space much more difficult. By paying attention to these four essential criteria, we are able to effectively enhance performance while adhering to appropriate time constraints. Based on empirical evidence, the literature in the field of medical image analysis consistently supports the notion that these four features have a major impact on performance [9]. Transferability: These hyperparameters can also be employed for other histopathological imaging studies, which means that the tuning procedure can be applied once more.

4. Methodology

Keras Tuner was employed for Bayesian optimization to efficiently explore the hyperparameter space by assessing the performance of various configurations and intelligently selecting the optimal ones [3]. A distinctive HyperModel class was developed to encompass both the CNN architecture and the hyperparameters. This enabled flexible experimentation and automatic optimization. The tuning methodology necessitated 25 trials for each model over eight CNN variants, representing an effective balance between expense and comprehensiveness. We enhanced the subsequent critical hyperparameters: What is the number of convolutional layers present. The model's ability to extract hierarchical features from histopathological images was enhanced by incorporating 3 to 7 layers, each containing 512 filters. Rate of learning:

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Configure to a value between 0.0001 and 0.01, allowing for the selection of the rate and stability of training convergence. The dropout rate ranged from 0.1 to 0.6 and was employed to mitigate overfitting and enhance the model's generalization. Optimizer selection: The tuning process evaluated various optimizers, including Adam, RMSprop, and SGD, to identify the most effective gradient-based update algorithm for the specific dataset and architecture employed.

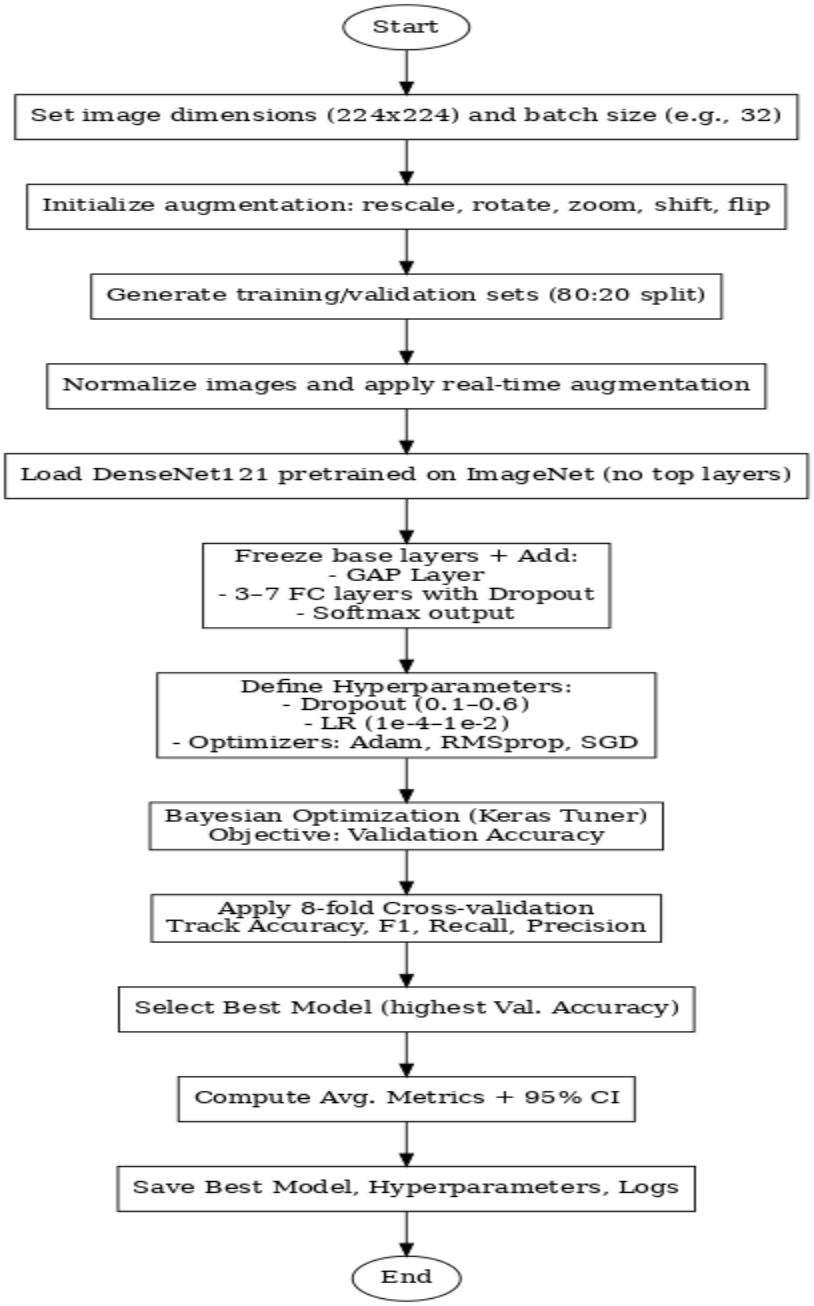

Figure 1: Steps in Hyper Parameter Tuning for DnseNet121

The selection of hyperparameter ranges and configurations was informed by insights from previous research and our experimental findings. The inclusion of optimizer selection in the tuning loop facilitated a thorough search, improving both network architecture and training

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dynamics[11]. This Bayesian tuning strategy maximized validation accuracy and ensured training efficiency, minimizing manual intervention and illustrating the advantages of automated hyperparameter optimization in medical image classification. The Python code implements a deep learning pipeline for hyperparameter tuning and evaluation of a CNN model utilizing Bayesian Optimization through the Keras Tuner framework. This approach aims to improve model performance, especially in multi-class classification tasks like histopathological image analysis, through the systematic selection of optimal hyperparameters. First, the necessary libraries from TensorFlow, Keras, and scikit-learn are imported. Examples include optimizers such as SGD, RMSprop, and Adam, alongside tools for early stopping, learning rate adjustment, and performance monitoring. The model is configured for image classification tasks across three default categories, utilizing standard parameters such as an image size of 224x224, a batch size of 16, and three output classes. Subsequently, two essential callbacks are established. EarlyStopping monitors the validation loss during training and halts the process if no improvement is observed for eight consecutive epochs. This prevents overfitting and reduces unnecessary effort. ReduceLROnPlateau automatically adjusts the learning rate when progress ceases. If the validation loss does not improve over five epochs, the learning rate is increased by a factor of 0.2. This adaptive learning rate schedule facilitates smoother convergence, particularly in complex loss landscapes.

The core segment of the code establishes a BayesianOptimization tuner through Keras Tuner. The tuner utilizes a custom MyHyperModel(), a class defined separately, which encapsulates the CNN architecture and delineates the range of hyperparameters for exploration. The tuner is configured to evaluate up to 25 distinct combinations of hyperparameters to identify the one that yields the highest validation accuracy (val_accuracy). All search results are archived in a specific local directory, enabling reproducibility and the oversight of experiments. The logging settings are adjusted to reduce the volume of logs generated by TensorFlow, thereby enhancing the readability of the training output. The MetricsCallback class is a specialized callback that extends beyond accuracy to compute F1 Score, Recall, and Precision following each epoch. The model obtains predictions from the validation dataset, compares these predictions to the ground truth, and employs scikit-learn's tools to calculate the relevant metrics. The variables are stored internally and monitored for each epoch, providing a clearer understanding of the model's performance, particularly in the context of imbalanced datasets commonly encountered in medical imaging.

Finally, the utility function create_tensorboard_callback establishes a dynamic logging directory for each fold in cross-validation settings, which stores TensorBoard logs that encompass training metrics and weight histograms. This facilitates the visualization of training dynamics in TensorBoard for each experiment or fold. The code exemplifies a structured, modular, and data-efficient deep learning workflow that incorporates hyperparameter optimization, performance evaluation, and training visualization, making it appropriate for tasks like gastric cancer image classification, where accuracy and generalization are essential. Indeed! This document presents a detailed algorithmic breakdown of the provided code, which

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implements Bayesian hyperparameter tuning and performance evaluation for CNN models utilizing Keras Tuner, incorporating advanced callbacks and metric logging.

Algorithm: Bayesian Hyperparameter Tuning for CNN with Advanced Metrics

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Step 1: Import Required Libraries

Import TensorFlow/Keras callbacks (EarlyStopping, TensorBoard, ReduceLROnPlateau)

Import optimizers (Adam, RMSprop, SGD)

Import Keras Tuner and related modules (BayesianOptimization, HyperParameters)

Import utility libraries (datetime, os, logging, numpy)

Import evaluation metrics (f1_score, recall_score, precision_score)

Step 2: Define Model Parameters

Set image input dimensions (img_height, img_width)

Define batch_size and num_classes for the dataset

Step 3: Configure Callbacks

Create EarlyStopping callback to stop training if validation loss doesn't improve for 8 epochs

Define ReduceLROnPlateau to decrease learning rate by a factor (0.2) after 5 stagnant epochs

Configure logging levels to suppress unnecessary TensorFlow output

---

Step 4: Define Bayesian Tuner

Instantiate BayesianOptimization tuner from keras_tuner

Pass in a custom HyperModel class (e.g., MyHyperModel) that defines model architecture and hyperparameter space

Set objective as 'val_accuracy'

Specify number of trials (e.g., 25)

Set directory and project name for saving tuning results

Step 5: Define Custom Metrics Callback

Create a class MetricsCallback that:

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Initializes empty lists to store loss, accuracy, F1 score, recall, and precision

At the end of each epoch:

Collect predictions on validation data

Calculate **F1 Score**, **Recall**, and **Precision** using sklearn.metrics

Append calculated values to internal lists

Log metrics for each epoch

Step 6: Configure TensorBoard Logging

Define a utility function create_tensorboard_callback(fold) to:

Set log directory based on current fold and timestamp

Return TensorBoard callback instance for visualization

Step 7: Execute the Tuning Process

Load dataset (training/validation)

Call tuner.search(...) with:

Input training data

Validation data

Epochs, batch size, and callbacks (early_stopping, reduce_lr, MetricsCallback, TensorBoard)

Retrieve best hyperparameters using:

best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

Step 8: Final Model Training & Evaluation

Build final model using best_hps

Train and evaluate the model on training/validation/test data

Optionally use metrics logged in MetricsCallback for performance comparison

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5. Result and Discussion

Medical image classification is a critical task in modern health care that aids in diagnosis, treatment planning, and patient care[12]. Hyperparameter tuning played a pivotal role in enhancing the classification accuracy of CNN models used for gastric cancer histopathological image analysis. To determine the optimal hyperparameter ranges, we applied Bayesian optimization using Keras Tuner. After that, we validated the performance using K-fold cross-

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validation. Using this approach, we were able to effectively and methodically fine-tune many CNN designs, striking a good balance between computational feasibility and model correctness. Important hyperparameters such as the optimizer, learning rate, number of dense layers, and dropout rate were tweaked for each CNN variant. The top performing model was DenseNet121, which included five custom dense layers, a learning rate of 0.0002, and a dropout rate of 0.1. The RMSprop optimizer improved convergence significantly by maintaining stable training by automatically adjusting the learning rates according to the size of the gradients. But EfficientNetB4 required more layers and had a higher dropout rate of 0.4, despite its power. The overfitting that occurred on very small medical datasets was likely caused by its numerous factors. The optimal learning rate for this architecture was determined to be 0.00018 using the Adam optimizer.

When it came to optimizing CNN architectures, RMSprop and Adam never let us down. The intricate interplay of model depth, regularization strength, and training dynamics is demonstrated by the fact that optimal settings varied among models. The deep feature extraction capabilities of VGG16 and VGG19, for instance, necessitated higher learning rates. Models with similar architecture but varied depths might exhibit various levels of performance; VGG16 achieved the greatest results at 0.001. To help you compare architectural needs and tuning outcomes, Table 3 summarizes the ideal hyperparameter choices for each CNN model. Our results show that with the right architecture-specific hyperparameter settings, models of any complexity can outperform their simpler counterparts.

Table 3 : Optimal hyperparameter settings for selecting the best CNN models

Model/Best Parameter	No. of Custom Layers	Leaning Rate	Dropout Rate	Optimizer
DenseNet121	5	0.0002	0.4	RMSprop
EfficientNetB4	7	0.0018	0.4	Adam
InceptionV3	5	0.0020	0.1	RMSprop
InceptionResNetV2	4	0.0001	0.4	RMSprop
MobileNetV2	4	0.0036	0.3	Sgd
ResNet50	4	0.0001	0.1	Adam
VGG16	5	0.0016	0.1	RMSprop
VGG19	3	0.0004	0.1	RMSprop

In comparison, our CNN-based approach for gastric cancer image classification—particularly the DenseNet121 model—shows superior performance in terms of accuracy, parameter efficiency, and model size. To further improve generalization and reduce overfitting, especially in small-scale datasets, future work could explore hybrid optimization strategies (e.g., Bayesian + Genetic) and layer-wise freezing during transfer learning.

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6. Conclusion

This research systematically illustrates the efficacy of Bayesian Optimization (BO) in hyperparameter tuning for Convolutional Neural Networks (CNNs) within the context of gastric cancer histopathological image classification. The research utilized Keras Tuner's Bayesian Optimization framework to identify optimal hyperparameter settings, resulting in enhanced model accuracy and reduced training time. This approach required significantly fewer evaluations compared to conventional tuning methods such as grid or random search. The experimental results indicate that modifying specific hyperparameters—specifically, learning rate, dropout rate, optimizer type, and number of dense layers—significantly improves classification performance. DenseNet121 exhibited the optimal balance of accuracy, computational efficiency, and model complexity among all tested designs. It was able to generalize well across images of multi-class stomach tissue. RMSprop and Adam are optimizers that enhance convergence stability. Adaptive learning rate schedules and regularization techniques, such as dropout, effectively mitigate overfitting, a critical consideration when dealing with limited medical datasets. The findings demonstrate that Bayesian Optimization serves as a computationally efficient alternative to exhaustive search methods and functions as an intelligent, data-driven framework capable of leveraging prior evaluations to effectively explore the hyperparameter space. The integration of this approach into the CNN development pipeline enables reproducible, automated, and high-performance model optimization, meeting the growing need for interpretable and resource-efficient medical AI solutions. The proposed method establishes a reusable mechanism for hyperparameter optimization in medical image analysis, particularly in applications utilizing histopathology for cancer detection. This investigation demonstrates the effectiveness of BO, affirming its suitability for clinical AI systems that require accuracy, reliability, and efficacy. Future research will seek to enhance this framework by incorporating hybrid optimization methodologies, specifically the integration of Bayesian Optimization with evolutionary algorithms, such as Genetic Algorithms or Particle Swarm Optimization, to improve exploration in high-dimensional environments. Layer-wise fine-tuning in transfer learning, combined with multi-objective optimization that prioritizes both accuracy and inference latency, may facilitate its application in real-time diagnostic environments. The integration of advanced models with explainable AI (XAI) modules, such as Grad-CAM and SHAP, will enhance the comprehensibility and reliability of clinical decision support applications.

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Conflict of Interest:

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