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Hyperband-Optimized Convolutional Neural Network Model for Efficient Brain Tumor Classification and Prediction

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Abstract

Human life depends heavily on health. Since the brain is the vital, distinctive and invaluable organ, its health is very crucial. A group of abnormal cells in the brain that might spread to other tissues and endanger life that is called a brain tumor. For treatment planning to be effective, a precise diagnosis is necessary. Like other organs, the health of the brain can also be analyzed with magnetic resonance images (MRI) for the purpose of diagnosis. Artificial intelligence can handle huge amounts of data. There are so many researchers who have developed various deep learning based models for addressing the brain tumor prediction issues. The model may take more no. of parameters and may lead more time to training the model. For addressing this issue, we have proposed the HB-optimized CNN model which automatically selects optimal hyperparameters, fine-tuning the CNN to achieve high prediction accuracy with minimal computational overhead. For evaluating the proposed approach, we have collected 3,000 MRI images from a publicly available dataset and the experiments are carried out using different optimization parameters. Lastly, experimental findings showed that our suggested model outperformed the conventional CNN, AlexNet, and VGG-16 Net models, achieving 88.23%, 91.15%, and 93.40%, respectively.The core novelty lies in integrating Hyperband optimization, which is used to dynamically fine-tune CNN hyperparameters by allocating computational resources efficiently and eliminating underperforming configurations early. Unlike traditional tuning methods such as grid search or Bayesian optimization, Hyperband offers a superior balance between exploration and exploitation, significantly reducing computational cost while maintaining high model performance. The proposed HB-CNN model is evaluated against well-known CNN architectures like AlexNet and VGG-16 and demonstrated with higher classification accuracy and faster convergence. This research establishes HB-CNN as an effective and efficient technique for MRI-based brain tumour diagnosis.

Keywords: Brain Tumor, Disease Classification, Optimization, Parameter Fine-tuning, Magnetic Resonance Image, Healthcare, MRI and CNN.

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1. Introduction

The most vital organ in the human body is considered to be the brain, a very complex structure. Neurons made of cell bodies can number in the billions inside of this structure.

A tumor is an aberrant collection of these brain cells that is made up of unchecked cell division and it is a cell growth inside or close to the brain. Brain tumors can be developed by brain tissues and nearer to it. The parts namely pituitary gland, pineal gland, brain surface membranes, and neural pathways are positioned adjacent to one another. Primary brain tumors are originating in the brain itself. On rare occasions, cancer can scatter to the brain from other parts of the body, which are known as secondary or metastatic brain tumors [1].

Primary brain tumors can be in various types. It is observed that not all brain tumors are cancerous. These are characterized as benign brain tumors which are noncancerous. As noncancerous brain tumors grow over time, they may compress brain tissue. Another type of brain tumors are malignant brain tumors which are brain cancers. Brain tumors have a rapid spread. Cancer cells have the ability to penetrate and damage brain tissue. Brain tumors can be very small or large in size. Because of the symptoms they provide, some brain tumors can be easily detected while they are quite tiny [2].

Before they are discovered, other brain tumors may increase in size. The brain is not as active in certain areas like others. There may be a chance that if the brain tumor is less active, a brain tumor may not immediately create symptoms. Based on the kind, location, and size of our brain tumor, our treatment choices will vary depending. Common treatments may include surgery and radiation therapy. There are several categories of brain tumors [3].

The sort of cells that comprise a brain tumor determines its type. Certain laboratory studies may yield information specific to the tumor cells. Using this information, the kind of brain tumor can be identified by the medical people. The brain tumors of malignant type usually develop quickly, although benign brain tumors frequently grow slowly. Therefore, the useful tool is required for brain tumor early detection and efficient treatment planning. Implementing an efficient treatment for brain tumors requires an accurate and timely diagnosis. The pathological type, grade, and stage of the tumor at diagnosis all influence choice of the treatment [4].

As the computer systems are often more efficient than people, contemporary computer algorithms in the medical sciences have recently achieved accuracy levels equivalent to those of human professionals. Artificial Intelligence (AI) is a growing field of computer science which is able to create intelligent machines that can perform tasks with human intelligence. Every day, humans are assisted by artificially intelligent devices. The few application domains of artificial intelligence include automated interfaces for recognition of speech, visual perception skills, decision-making ability, and language translation capability [5]. AI is a diverse field of research. Artificially intelligent technologies are employed in the healthcare domain for enhancing the patient experience and their care. AI assistants are also being used to support doctors. There is great hope that AI is able to improve the healthcare industry in many ways, including not just medication development, patient diagnosis, and prognosis, but also acting as a physician's assistant and using the experience they can give treatment with more care to patients.

AI can help in the identifying and treatment of complex conditions like brain tumors by integrating fields like big data analytics and AI branches of machine learning, and deep learning by using brain imaging methods like MRI. The AI may identify and classify cancers. Tumor size, location, class, and aggressiveness may all be ascertained with the use of AI algorithms [6]. Patients have a greater understanding of their health, and doctors are able to diagnose and treat patients more accurately.AI may also be used to monitor a patient's therapy progress. Predicting possible tumor recurrence and evaluating treatment response are two applications of AI-based analytics. This allows for the development of customized treatment strategies and the more efficient organization of patients' treatment programs. This research has adapted the CNN architecture with Hyperband for MRI-based brain tumor classification and introduced a domain-specific, performance-optimized model for critical healthcare applications. Unlike conventional deep learning models that require extensive trial-and-error for parameter tuning, HB-CNN significantly reduces computational overhead by leveraging Hyperband's early-stopping mechanism. The proposed model demonstrates improved classification accuracy over traditional architectures such as AlexNet and VGG-16, highlighting the effectiveness of Hyperband-guided optimization in medical image analysis.

Brain tumor classification using MRI is a critical task in medical diagnostics, where accurate and timely detection can significantly influence patient outcomes. While Convolutional Neural Networks (CNNs) have shown considerable promise in this domain, their performance heavily depends on the selection of optimal hyperparameters—often determined through computationally expensive and static search methods such as grid search, random search, or manual tuning. These methods are time-consuming and also lack adaptability and scalability when applied to high-dimensional hyperparameter spaces common in deep learning models. Moreover, many existing studies overlook the need for efficient optimization frameworks that can dynamically balance resource allocation and accuracy. This research addresses these gaps by introducing Hyperband optimization into the CNN training pipeline, offering an adaptive, resource-efficient solution that maintains or even improves diagnostic performance. Our work is aimed to bridge the gap between high-performance model training and practical deployment needs in clinical environments.

The organization of the document is as follows: The literature survey is provided in the second part. The third part explains the proposed methodology of this research work. The experimental results are shown in the fourth part. At last, section 5 discusses and describes the research's conclusion.

2. Related Works

AI systems are being used in medical imaging to analyze Computed tomography images, x-rays, MRI images, and other images in order to detect abnormalities or other findings that a human radiologist might overlook. Applications in healthcare now heavily rely on AI. It helps the doctor make judgments regarding medications, therapies, mental health, and other requirements of patients. Several researchers have developed various methodologies in healthcare use cases using AI which becomes more dominant. This section describes methodologies that have been given by various researchers.

Deepak et al., [7] have proposed a classification system that has used a pre-trained GoogLeNet which extracted features from brain MRI images. The researchers have used SVM and KNN models for extracting Deep CNN features and used dataset from Fig share. Anantharajan et al [8] proposed the EDN-SVM method based on DL and ML for brain tumour detection in MRI. Adaptive Contrast Enhancement Algorithm (ACEA) and median filter were applied in which MRI images were collected and pre-processed. Fuzzy c-means based was used for segmenting the pre-processed images and Gray-level co-occurrence matrix (GLCM) was used for energy, mean, entropy and contrast features extraction. Then, abnormal tissues were classified using the classifier.

Mahmud et al., [9] designed CNN architecture for identifying brain tumors using MR images efficiently. They have also discussed other models of ResNet-50, VGG16, and Inception V3 and experiments were conducted. Then in the validation stage, the holdout validation system has been used. The various machine learning methodologies have been used to train images. The four following different types of brain images viz: glioma tumor, meningioma tumor, no tumor, and pituitary tumor have been tried to validate.

A DCNN model to identify brain cancers was presented by Musallam et al. [10] using an MRI dataset. Iterations, max-pooling, and a few convolutions have been used in a lightweight model. Additionally, CNN-SVM, VGG16, and VGG19 have been examined. Using BRATS MR data, Sajid et al. [11] have proposed a hybrid CNN model to identify brain tumors. The efficiency of advanced regularization methods like dropout and a special two-phase training procedure has been analyzed and validated. They suggested a hybrid model that upgraded the model's performance which combines two and three path networks. Two DL models were created to detect brain cancers that are multiclass (meningioma, glioma, and pituitary) and binary (normal and abnormal) [12]. Two publicly available datasets that are including 3064 and 152 MRI images have been used. In the proposed model 23-layers convolutional neural network is used with the 1st dataset. A 23-layers CNN architecture is used for the second data set. For dealing with overfitting problems, transfer learning is used and they combine VGG16 architecture.

Pashaei et al., [13] suggested different models for identifying meningioma, glioma, and pituitary tumors. In the proposed model, a CNN extracts hidden features from images and selects features. It uses 4 convolutional layers, 4 pooling layers, 1 fully connected layer, and 4 batch normalization layers. Also,in their study, the dataset provided by Cheng has been used. The 10-fold cross validation method was used for evaluation. Nayak et al., [14] has developed CNN based dense EfficientNet for detecting brain tumor images using MRI. Also, their research experimented ResNet-50, MobileNet, and MobileNetV2, using dense EfficientNet and have obtained an accuracy of about 89.78%.

Wozniak et al., [15] developed an innovative correlation learning mechanism (CLM) for DNN architecture which has combined CNN with classic architecture. It helped CNN to find more efficient filters for pooling and convolution layers. Therefore, the main neural classifier has learnt faster and reaches higher efficiency. Their evaluation results showed that their proposed CLM model has reached accuracy of 96%. In a separate study, A multiple path 3D FCN model technique was provided by Sun et al. [16] for the segmentation of brain tumours via 3D dilated convolution in each path, it has extracted different receptive fields of feature maps from multi-modal MR images. These features have subsequently been spatially integrated via skip connections. The model's capacity to identify the borders of tumour areas has been made easier by this paradigm. But because direct relationships between high-level and low-level characteristics and the semantic distinctions between encoders and decoders would provide surprising results, the model needed a post-processing step.

The efficiency of DL learning architectures to improve brain tumour diagnostic accuracy is explored [17]. A ML approach of transfer learning enabled them to apply previously trained models to new problems. This is especially helpful in medical imaging applications, where labeled data is frequently limited. This research has evaluated four different TL architectures: MobileNetv3, DenseNet169, VGG19, and ResNet152. A dataset from the benchmark database Kaggle has been used to train and evaluate the models. Both training and testing were conducted by 5-fold cross validation. The four categories of data —pituitary, normal, meningioma, and glioma—were subjected to image enhancement techniques in order to improve the dataset's balance and the models' performance. MobileNetv3 outperformed other current techniques by achieving the maximum accuracy of 89.75%. This has shown how deep TL systems have the power to completely transform the diagnosis of brain tumors.

CNN and other feature-based or data-driven algorithms might not perform like cascaded algorithms. Handcrafted feature-based ML algorithms have been employed in a unique cascaded way [18] to intelligently provide CNN with historical data. Each patient received 4 MRI modalities of T1, T1c, T2, and FLAIR in addition to manual ground truth. Brain tumors were separated using a Global Convolutional Neural Network that incorporated DL and hand-crafted features. Two CNNs in parallel, CSPathways CNN (CSPCNN) and MRI Pathways CNN (MRIPCNN), have been used in the proposed GCNN architecture to properly segment BraTS brain tumors. The proposed model has performed 87% better than the state of the art.

Ullah et al., [19] have proposed an evolutionary lightweight model that has combined multiple XGBoost decision trees. A final prediction is generated by combining the weak predictions from each XGBoost decision tree with the predictions of other XGBoost trees. Different subsets of multimodal data can be used to train the various XGBoost algorithm instances. The BraTS 2020 dataset was utilized to evaluate the suggested model. 285 MRI scans of patients with gliomas are included. According to the evaluation data, they used four grades and attained 93.0% accuracy. The Table 1 shows some methodologies and the accuracies of existing research of brain tumor detection. Besides the above, Many machine learning methods are used to classify MRI images by Rehman et al. [26]; Zhou et al., [27]; Kumar et al. [28]. Several deep learning techniques have been applied for MRI image diagnosis according to the literature study [29-33].

Table 1. Literature Survey of Brain tumor Classification

S. No.	Authors	Methodology	Dataset	Accuracy
1.	Gull et al., [20]	Deep learning	MRI from the cancer imaging	95.5%
2.	R Hashemzehi et al [21]	CNN Model	3064 T1-weighted CE-MRI	95%.
3.	Taher et al.[22]	CNN-Brain Tumor-net	MRI dataset	85%
4.	Suvashisa et al., [23]	Neural network	Dataset-255	89.12
5.	AlsubaiShtwai [24]	CNN-LSTM	Kaggle MRI brain tumor	89.1%
6.	Alsaif et al., [25]	VGG	MRI dataset	83%

3. Proposed Work

In this section, our objective is to create a robust and optimized model capable of effectively differentiating among types of brain tumors using Magnetic Resonance Imaging (MRI) images. The proposed methodology presents a structured and optimized framework for developing a Hyperband-Optimized Convolutional Neural Network (CNN) model aimed at the efficient classification and prediction of brain tumors. As shown in Figure 1, the proposed methodology consists of following stages as mentioned below:

- Collecting Dataset
- Pre-processing the dataset
- Building the CNN model
- CNN HB-optimization strategies
- Predicting the Results.

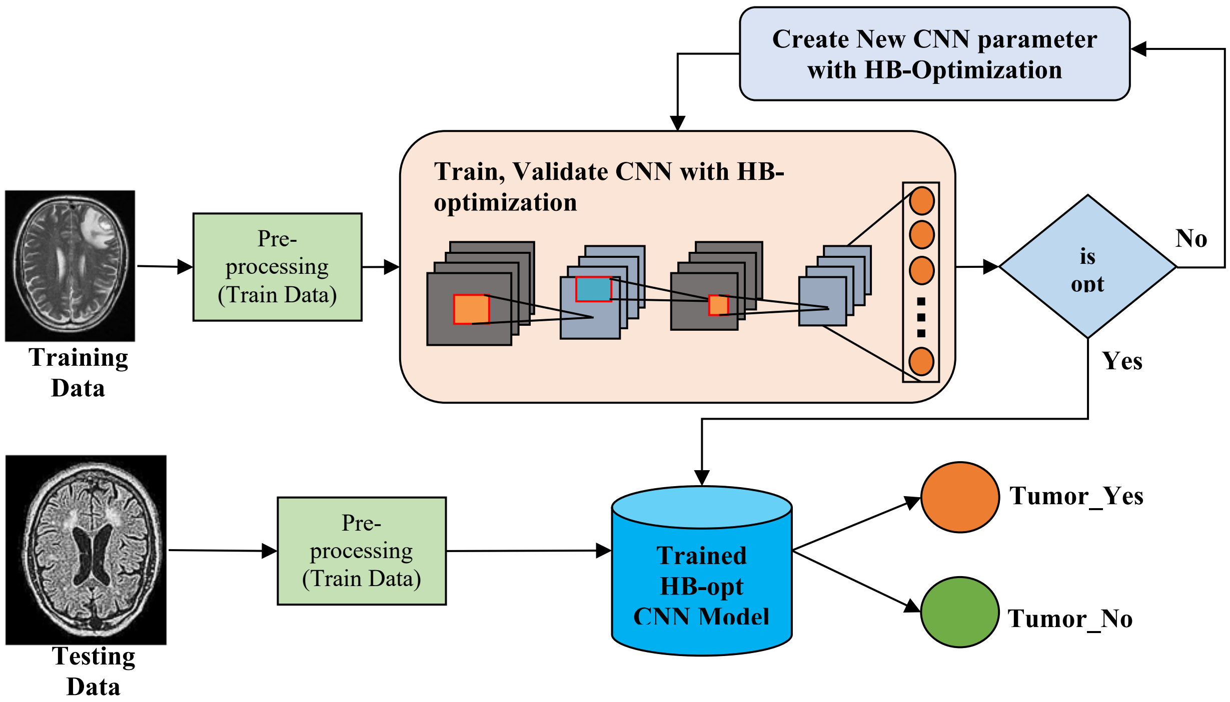

Figure 1. Architecture of brain tumor disease prediction model

3.1. Collecting Brain Tumor Dataset

The research has been leveraged publicly accessible brain tumor MRI dataset from Kaggle [34]. It provides a comprehensive breakdown of these datasets, including

their class distributions and the allocation of images for training, validation and testing. The dataset consists of 3,000 images, divided into "Tumor_No" and "Tumor_Yes" classes. The training set contains 2,400 images, while the remaining 300 images are used for validation and 300 images used for testing as illustrated in Table 2. The sample brain tumor images are shown in Figure 2.

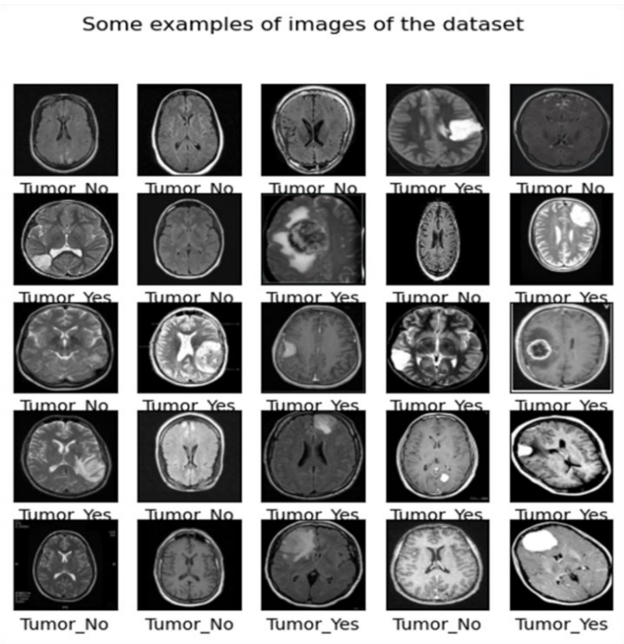

Figure 2. Architecture of brain tumor disease prediction model

Table 2. Dataset Split ratio

S. No.	Disease Type	Tr. Images	Val. Images	Test	Total
1.	Tumor_No	1200	150	150	1500
2.	Tumor_Yes	1200	150	150	1500

3.2. Pre-processing the Dataset

The Data preprocessing begins by loading MRI images and enhancing dataset variety through unique data augmentation techniques. These may include random rotations, mirroring, zooming, brightness/contrast shifts, and slight Gaussian noise addition to simulate imaging variability.

Each image is then resized to a uniform resolution, with 128×128 pixels, optimizing the model for consistent input size and computational efficiency. After resizing, pixel values are normalized to a [0,1] scale to standardize input. The distribution of brain tumor image in each class is shown in Figure 3.

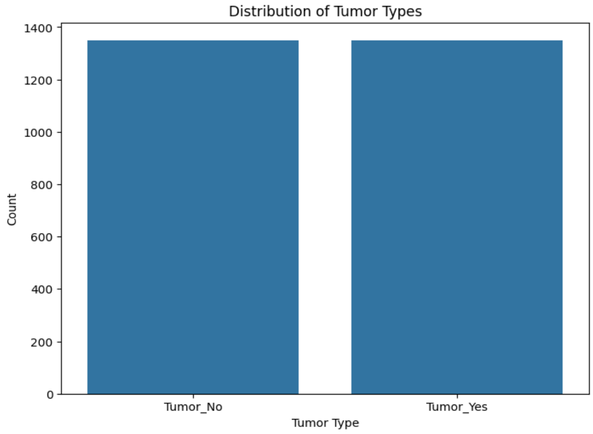

Figure 3. Distributions of tumor types

3.3. Building CNN Model

The CNN is one the important models in classification tasks. The CNN model which consists of following sequence of layers:

- Feature Extraction Layer
- Feature Reduction Layer
- Transformation Layer
- Fully Connected Layer
- Soft-max Classifiers

Feature Extraction Layer: From MRI pictures, it automatically finds and learns key characteristics. To capture spatial information like edges, textures, and forms, CNN convolutional layers (Conv2D) filter the input imagine with kernels [31-36]. Convolution uses a kernel (filter) to generate feature maps with particular visual information. First, edges and corners are found. Tumor borders and areas of interest arise from these low-level characteristics as the network depth grows.

Feature Reduction Layer: The Feature Reduction Layer is reducing feature maps's dimensionality that is created by the feature extraction layers while keeping important characteristics. By reducing model complexity and computing efficiency, the reduction layer can reduce overfitting.

Transformation Layer: The Flatten operation turns 2D feature maps into 1D feature vectors for completely linked layers. To create final predictions, the neural network must process information linearly.

Fully Connected Layer: The Fully Connected (Dense) Layer helps for learning complex patterns and associations between the extracted features.

Soft-max Classifier: CNN final layers employ the Softmax Classifier for binary-class classification problems like brain tumor classification. Softmax translates fully connected layer output into class probability distributions. For brain tumor categorization, the network must predict no tumor and tumor. The last dense layer's outputs are converted into class probabilities via the Softmax algorithm.

3.4. Hyperband-CNN Model

In this subsection, we have proposed the HB- optimized CNN model that automatically selects optimal hyperparameters, fine-tuning the CNN to achieve high prediction accuracy with minimal computational overhead. Table 3 highlights the Hyperband optimization parameters determined for enhancing the performance of the model. The architecture is composed of 3 convolutional layers, which effectively capture spatial features from the input data. The number of filters for these layers is set as {64, 64, 32}, ensuring a gradual reduction in feature map complexity, which balances computational efficiency and feature extraction capabilities.

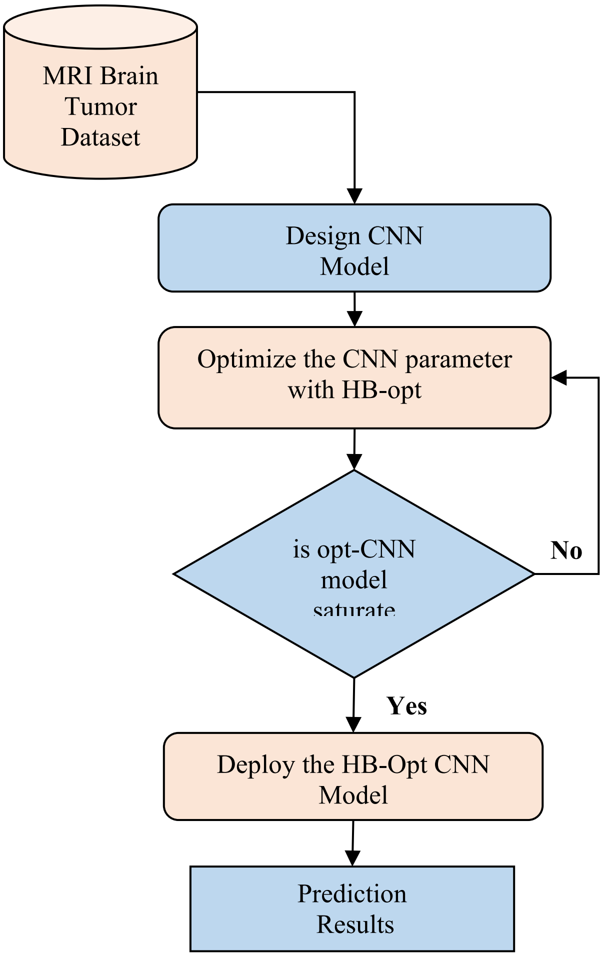

Figure 4. HB parameter optimization strategies

The convolutional layers utilize two kernel sizes: 3x3 and 5x5, ensuring a balance between capturing fine-grained local patterns and broader spatial features, thereby enhancing the model's capacity for understanding complex data. In dense layer, multiple configurations were explored, including sizes of 64, 128, 196, and 256 units, to determine the optimal feature representation. Similarly, to prevent overfitting and improve model generalization various dropout rates (0.2, 0.3, and 0.4) were tested.

Table 3. Parameter Optimization

S. No.	Parameter Name	Parameter Range	Best Parameters
1.	Conv Layer	{1,2,3}	3 Conv Layer
2.	No. of Layer	{32, 64}	{64,64,32}
3.	Kernel Size	{3,5}	5x5
4.	Dense	{64, 128, 192, 256}	64
5.	Dropout	{0.2, 0.3, 0.4}	0.4
6.	Optimizer	{‘Adam’, ‘RMSProp’}	RMSPRop

For optimization, both Adam and RMSProp algorithms were evaluated. As shown in Figure 4, these optimized parameters were identified through extensive experimentation using the Hyperband algorithm, ensuring that the model achieves the best possible balance between accuracy, efficiency, and generalization for the given classification task.

4. Experimental Results and Analysis

The Hyperband-Optimized Convolutional Neural Network (CNN) model of brain tumor prediction and classification leveraged several essential libraries, including TensorFlow and Keras for model development, NumPy and Pandas for the data manipulation, OpenCV for image processing, Scikit-learn for the evaluation metrics and hyperparameter tuning, and Matplotlib and Seaborn for visualization. The experiments were conducted on a powerful machine equipped with an Intel Core i7-9700K CPU, an NVIDIA GeForce RTX 3060 GPU with 12 GB of VRAM, 16 GB of DDR4 RAM, and a 1 TB SSD device.

4.1. Performance Metrics

For evaluating the performance of a CNN model for brain tumor disease diagnosis and prediction systems, consider these key performance metrics:

Accuracy: It measures the proportion of correct predictions to the total no. of samples.

$$\alpha = \frac{TP+TN}{Total\ Samples} \quad (1)$$

Precision: The ratio of true positives to the total predicted positives, indicating the accuracy of positive predictions.

$$\beta = \frac{TP}{TP+FP} \quad (2)$$

Recall: Recall also known as sensitivity, highlights the model's ability to capture all relevant instances, represented as:

$$\gamma = \frac{TP}{TP+FN} \tag{3}$$

F1-Score: It provides the harmonic mean of precision and recall (ie) a balance between the two metrics.

$$\delta = 2 \times \frac{\beta \cdot \gamma}{\beta + \gamma} \tag{4}$$

4.2. Results and Discussions

The experimental results were derived using Hyperband optimization, an efficient technique that evaluates multiple parameter configurations by dynamically allocating resources to the most promising candidates. This approach reduces computational overhead compared to traditional grid search methods. Hyperband optimization identified the best model architecture as having 3 convolutional layers, which effectively captured hierarchical features. For the number of filters, the configuration {64, 64, 32} provided the optimal balance between feature extraction and computational efficiency. The kernel sizes 3x3 and 5x5 were tested, with 5x5 performing better by capturing broader spatial features.

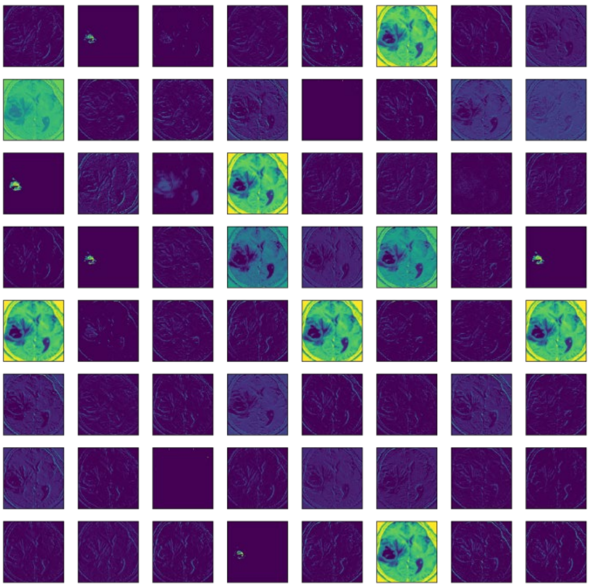

Figure 5. Feature visualization of Tumor images

For the dense layer, Hyperband evaluated sizes {64, 128, 192, 256} and selected 64 units as optimal, balancing simplicity with performance. Dropout rates of 0.2, 0.3, and 0.4 were analyzed, with 0.4 offering the best regularization and preventing overfitting. Between the optimizers Adam and RMSProp, the latter was chosen for its faster convergence and better handling of noisy gradients. The feature visualization of brain tumor image is shown in Figure 5.

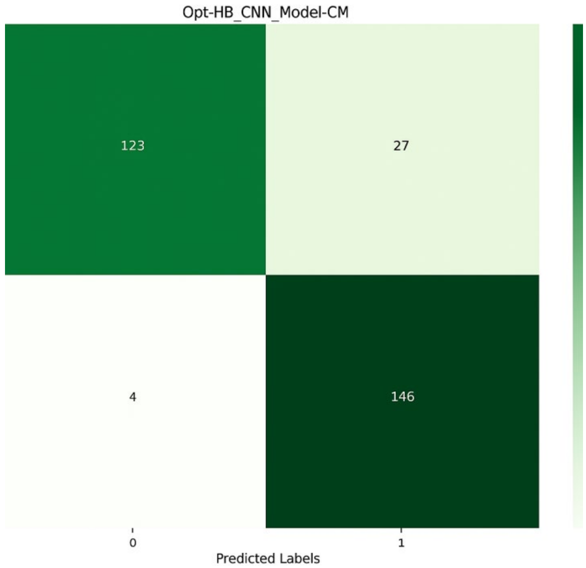

Figure 6. CM of proposed HB-CNN Model

One of the classes has been incorrectly classified, as demonstrated in confusion matrix(CM) of Figure 6, using HB-optimized CNN model. An example of this would be the misclassification of tumor_no as tumor_yes. We have optimized CNN model using HB optimized CNN model for increasing the prediction accuracy of the brain tumor disease prediction.

Table 4. Best HB Parameter Optimization

S. No.	Parameter Name	Best Parameters
1.	Conv Layer	3 Conv Layer
2.	No. of Layer	{64,64,32}
3.	Kernel Size	5x5
4.	Dense	64
5.	Dropout	0.4
6.	Optimizer	RMSPRop

With the use of the findings presented in Table 4, we were able to determine that the HB-optimized CNN model is the most efficient approach, having achieved the highest possible accuracy of 98.5%.

Table 5. Performance of proposed HB method

S. No.	Model	α	β	γ	δ
1.	CNN	88.23	87.9	88.15	88.10
2.	Alex Net	91.15	90.75	90.50	90.65
3.	VGG-16 Net	93.40	93.15	93.25	93.20
4.	HB-CNN Net	98.5	98.1	98.4	98.25

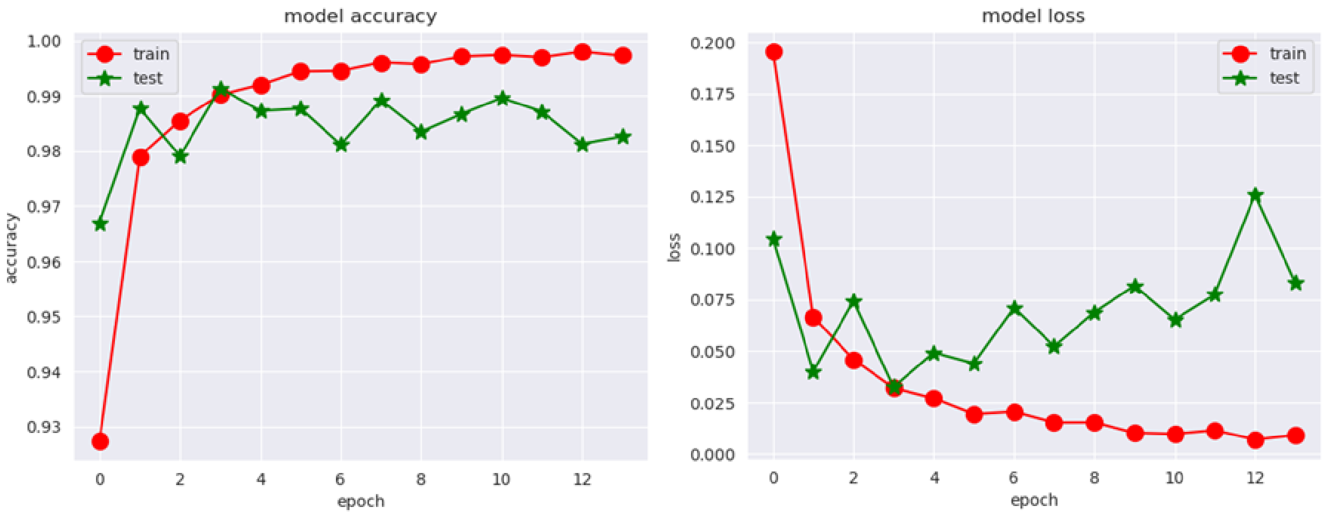

Figure 7. Training validation accuracy and loss of proposed HB-CNN Model

As shown in Figure 7, using the standard metrics of trained and validated accuracy, trained and validated loss are assessed after 15 epochs. The sample prediction result of proposed optimized HB-CNN model is shown in Figure 8.

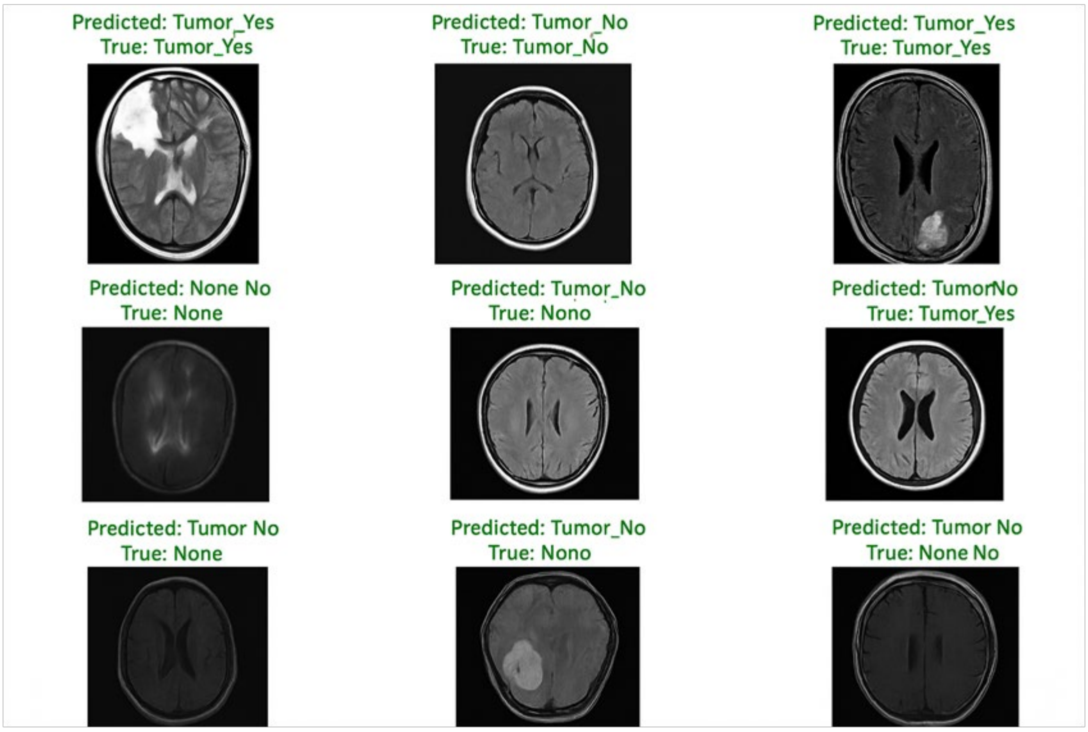

Figure 8. True prediction of results analysis

4.3. Comparison of Training and Computational Efficiency

To evaluate the computational efficiency of the proposed HB-CNN model, we compared its training time and resource usage against standard CNN architectures including AlexNet and VGG-16. All models were trained under identical hardware conditions. The results indicate that HB-CNN achieved convergence approximately 30–40% faster than VGG-16 and 20% faster than AlexNet, primarily due to the early-stopping and adaptive resource allocation strategies embedded in the Hyperband optimization process. Additionally, HB-CNN required fewer total training epochs on average, as underperforming configurations were quickly discarded, allowing computational resources to be focused on promising candidates. This demonstrates that HB-CNN not only improves classification performance but also offers a computationally efficient training pipeline, making it well-suited for real-world deployment in time-sensitive and resource-constrained clinical environments.

Table 6. Performance of proposed HB method

S. No.	Model	α	Avg. Training Time in (Hrs)	Epochs to Coverage
1.	CNN	88.23	6.1	70
2.	Alex Net	91.15	4.2	50
3.	VGG-16 Net	93.40	6.5	65
4.	HB-CNN	98.5	3.0	35

Conclusion

In this research, we have developed a HB-optimized CNN model which has demonstrated remarkable effectiveness in addressing the challenges of brain tumor prediction. By leveraging Hyperband optimization, the model automatically selects the best hyperparameters, ensuring high prediction accuracy while minimizing computational overhead. This strategy improves the efficiency of training but also outperforms traditional models like CNN, AlexNet, and VGG-16 in terms of accuracy. Experimental evaluations using 3,000 MRI images from a publicly available dataset showed that the proposed methodology has achieved prediction accuracies of 98.85%, 98.35%, and 98.18% respectively, excels in performance while comparing other models.

Beyond its technical performance, the practical implications of HB-CNN are noteworthy. Its high diagnostic accuracy and optimization efficiency make it a strong candidate for integration into real-time clinical decision-support systems (CDSS), where rapid and reliable image-based diagnosis is critical. The lightweight tuning mechanism also makes HB-CNN suitable for deployment in resource-constrained healthcare settings, such as rural or mobile diagnostic units. Future work will focus on expanding the model's generalizability across diverse datasets and incorporating explainability features to further support clinical interpretability and trust. As a result of this research, hyperband optimized convolutional neural network system can be used for efficient brain tumor classification and prediction.

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