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A Combined Framework for Medical Image Classification and Detection of Brain Abnormalities Utilizing K-Nearest Neighbors and an Enhanced Convolutional Neural Network

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Abstract: The detection of abnormalities in medical images plays a pivotal role in early diagnosis and treatment. This paper presents a hybrid approach that combines K-Nearest Neighbors (KNN) and deep learning techniques to improve medical image classification and anomaly detection. The method applies KNN for classifying images such as MRI, CT, and X-ray scans, focusing on abnormality detection in brain images. By integrating KNN classifiers with feature extraction methods, the approach addresses challenges such as class imbalance and small datasets, resulting in improved detection accuracy. The effectiveness of the proposed method is demonstrated on a medical image dataset, showing significant improvements in both classification and anomaly detection tasks.

Keywords: Image Processing, Deep Learning, KNN, Medical Modalities, Abnormality

I. Introduction

Medical imaging plays a critical role in diagnosing and monitoring various diseases. Medical images from modalities such as MRI, CT, X-rays, and ultrasound are commonly used to detect abnormalities, including tumors, lesions, and fractures. However, accurately identifying these anomalies remains challenging, particularly in cases of imbalanced datasets or subtle features. Traditional classifiers such as K-Nearest Neighbors (KNN) have been widely applied in medical image classification. Despite its simplicity, KNN offers notable advantages due to its non-parametric nature and ability to manage complex, high-dimensional data.

The data is imbalanced (i.e., some categories have very few samples compared to others).

Abnormalities are subtle or hard to detect.

Small sample sizes limit the model's learning capacity.

This paper proposes a hybrid method that combines K-Nearest Neighbors (KNN) with deep learning techniques, specifically convolutional neural networks (CNNs), for feature extraction and classification. The approach targets abnormality detection across medical imaging tasks, addressing challenges such as class imbalance, noisy data, and limited sample sizes.

Related Works

Numerous studies have investigated the application of K-Nearest Neighbors (KNN) for medical image classification. For example, one study integrated KNN with feature extraction techniques to improve abnormality detection in chest X-ray images [1], while another applied KNN classifiers for Alzheimer's disease diagnosis using MRI data, demonstrating its robustness in small-sample and class-imbalanced scenarios [2]. Although KNN shows promise in classification tasks, its limitations—such as computational complexity and sensitivity to noise—can be mitigated by combining it with deep learning methods capable of automatic feature extraction.

The KNN algorithm has been applied across various medical imaging tasks, including cancer detection and neurological disorder diagnosis. Many studies combine KNN with other machine learning techniques, such as convolutional neural networks (CNNs) or support vector machines (SVMs), to enhance classification accuracy, demonstrating the benefits of hybrid models in medical image analysis. A review paper [4] discusses diverse applications of KNN in medical image classification and abnormality detection, covering fields such as tumor detection, brain imaging, and cardiovascular conditions.

A study introduced a hybrid model combining KNN and support vector machines (SVM) for brain tumor detection in MRI images. This approach improved detection accuracy by leveraging the strengths of both classifiers, outperforming standalone methods [5]. Additionally, another study applied KNN to detect skin cancer in dermoscopic images, emphasizing the role of texture-based feature extraction and demonstrating that KNN can achieve high detection accuracy for skin lesions [6].

The KNN algorithm has been applied for the early detection of lung cancer in CT scans by extracting features such as shape and texture, demonstrating its effectiveness in classifying and detecting lung cancer at early stages [7]. A study applied KNN for abnormality detection in colonoscopy images, identifying regions that may indicate the presence of polyps or other colorectal conditions [8].

Additionally, a hybrid approach combining convolutional neural networks (CNNs) and KNN has been tested for tasks such as tumor detection in MRI and CT scans. This hybrid method outperforms traditional approaches by leveraging both deep learning

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and machine learning techniques [9]. Another hybrid model combines KNN and SVM for breast cancer detection in mammogram images, achieving higher detection accuracy critical for early diagnosis [11].

Research on Alzheimer's disease detection using MRI scans proposes a framework for preprocessing MRI data and applying KNN to classify different stages of the disease [12]. Enhancements to KNN for mammogram image classification have incorporated advanced feature extraction techniques, improving accuracy in breast cancer detection.

An end-to-end learning strategy has been proposed that integrates KNN with feature extraction, improving performance on small-class and class-imbalanced medical datasets. This paper introduces a novel method combining deep learning and KNN for medical image classification, leveraging the strengths of both techniques [13].

Moreover, a hybrid CNN model has been developed to extract meaningful features from wireless capsule endoscopy images, achieving high classification accuracy in detecting gastrointestinal abnormalities. Another study applies deep CNNs for automatic feature learning and classification of mammogram images, achieving high accuracy in detecting calcifications and masses. Additionally, a method combining contrastive learning with radiomics features enhances abnormality classification and localization in chest X-ray images through a knowledge feedback loop, focusing on improving breast cancer detection from mammograms [15].

Lastly, a study investigates the application of KNN for skin cancer detection in dermoscopic images, demonstrating its promising results for effective classification of skin lesions [16].

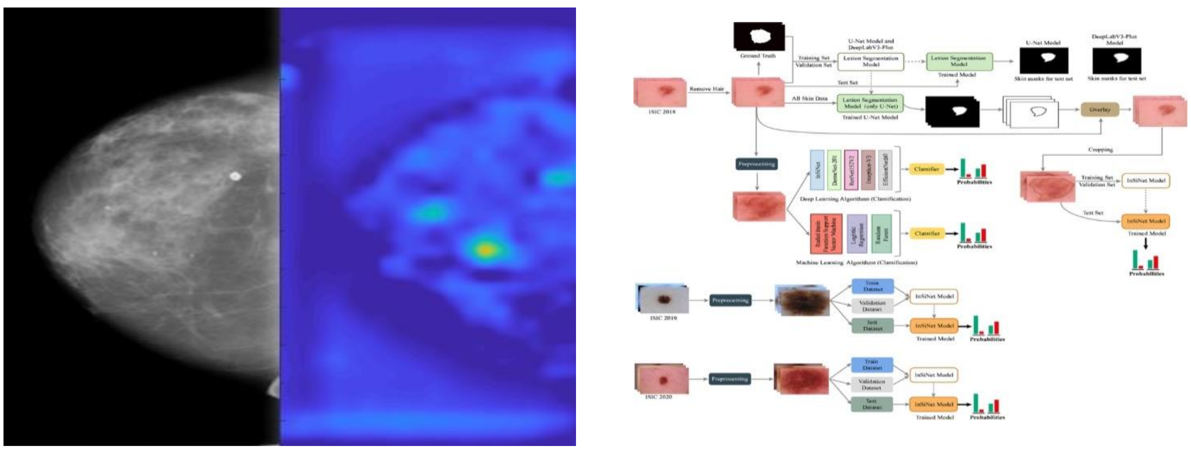


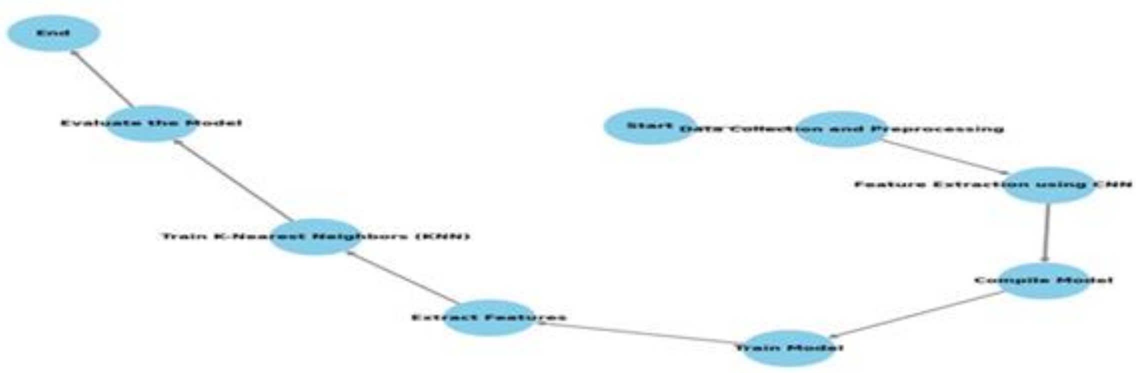
Fig. 1. Calcification localization results

II. Methodology

In this section, we discuss the methodology, which is divided into sequential steps, as outlined below:

Introduction to the Problem:

The primary goal of this work is to develop a hybrid approach for detecting and classifying abnormalities in medical images using a combination of Convolutional Neural Networks (CNNs) and K-Nearest Neighbors (KNN). We leverage powerful feature extraction capabilities of deep learning models like ResNet50, followed by KNN for classification. This approach combines the strengths of deep learning, which excels at learning rich features from data, with the simplicity and interpretability of KNN for improved classification performance.



In this research, we utilized a Brain MRI dataset to develop an innovative methodology for detecting and classifying abnormalities by integrating the k-Nearest Neighbors (k-NN) algorithm with an advanced Convolutional Neural Network (CNN). We began by loading and preprocessing the images, focusing on those labeled with varying levels of abnormality. The

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implementation was carried out in Python, using libraries like scikit-learn, OpenCV, and NumPy. The dataset was then split into training and testing subsets, with a 70-30 ratio. Finally, we trained the k-NN model for brain abnormality classification using scikit-learn's implementation.

Step-by-Step Breakdown of the Algorithm: Flowchart 1 shows the different steps of our method, and in the next section, these steps will be clarified.Flow Chart1.proposed method

Data Collection and Preprocessing:

Loading Data: The first step is to load the data from the specified directories. Typically, the images are organized into different subdirectories (e.g., one for each class in classification tasks). For this study, we use the MRI Brain Dataset, a publicly available medical image dataset focused on anomaly detection. All images are pre-processed to ensure consistency in resolution, noise removal, and normalization. Additionally, we balance the class distribution by augmenting the minority class using techniques such as rotation, flipping, and zooming. Data preprocessing and augmentation are essential for training deep learning models, as they enhance the model's robustness and ability to generalize.

Data Augmentation: Using the ImageDataGenerator to augment the training dataset is crucial, as it artificially expands the training set by applying transformations such as rotations, shifts, flips, and zooms. This process helps prevent overfitting and enhances the model's generalization capabilities.

For validation data: Only rescaling is applied because the validation set must remain unchanged in order to evaluate performance on the original data.

Feature Extraction:

We employ a convolutional neural network (CNN), such as ResNet or VGG, to extract features from raw medical images. These features capture high-level representations, making them more suitable for K-nearest neighbor (KNN) classification. This process significantly reduces the dimensionality of the dataset while preserving critical information for accurate classification.

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) have been crucial in advancing image recognition tasks, with influential architectures such as VGGNet and ResNet introducing design principles that significantly enhance performance. VGGNet, developed by the Visual Geometry Group at the University of Oxford, emphasizes depth by using small 3×3 convolutional filters. The architecture consists of several stacked convolutional layers followed by ReLU activation functions, interspersed with 2×2 max-pooling layers for spatial down-sampling. This design enables the network to capture intricate features by increasing depth while maintaining manageable computational complexity. Notably, VGGNet achieved great success in the 2014 ImageNet Large Scale Visual Recognition Challenge (ILSVRC), securing top positions in both localization and classification tasks [17].

ResNet addresses the challenges of training very deep networks, such as the degradation problem, where adding more layers can increase training error. The core innovation of ResNet is the residual learning framework, which incorporates shortcut connections that bypass one or more layers. These identity mappings allow the network to learn residual functions, enabling the training of much deeper networks without performance degradation. ResNet models, with depths of up to 152 layers, demonstrated superior performance on the ImageNet dataset and won the 2015 ILSVRC classification task [18].

K-Nearest Neighbors Classifier

The k-Nearest Neighbors (k-NN) algorithm is a fundamental non-parametric, supervised learning method utilized for both classification and regression tasks in machine learning. It operates on the principle that data points with similar features tend to reside in close proximity within the feature space. The algorithm classifies a new data point based on the majority class of its 'k' nearest neighbors in the training dataset [19]. KNN is applied to the extracted features to classify medical images into various categories. In our approach, we experiment with different K values to optimize classification performance. The KNN classifier is particularly well-suited to handle anomalies in datasets with skewed class distributions, making it effective for detecting anomalies in medical images. This algorithm has two phases:

Training Phase:

K-NN is an instance-based learning algorithm, meaning that it does not involve an explicit training phase. Instead, it stores the entire training dataset, which is utilized during the prediction phase.

Prediction Phase:

the algorithm computes the distance between the query and all points in the training set. Common distance metrics include Euclidean, Manhattan, and Minkowski distances.

The k-nearest neighbors (k-NN) algorithm assigns a query point to the most common class among its 'k' nearest neighbors for classification tasks, or the predicted value is the average (or weighted average) of the values of the 'k' nearest neighbors for regression tasks. Choosing the right value for 'k' is important; a small 'k' can be sensitive to noise, while a large 'k' may smooth out class boundaries. Cross-validation techniques are often used to find the optimal value of 'k'. The effectiveness of k-NN depends on the distance metric, which should match the nature of the data and problem domain. Since k-NN relies on distance calculations,

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features with larger scales can disproportionately affect the results, so normalization or standardization of features is recommended. While k-NN is easy to understand and implement and can be applied to both classification and regression tasks, it can be computationally expensive, especially with large datasets, as it requires calculating the distance between the query and all training samples. Storing the entire training dataset can also be memory-intensive. Additionally, irrelevant or redundant features can negatively impact the performance of k-NN [20].

Experiments and Results of Proposed Hybrid Approach

The hybrid model combines KNN with deep neural networks, trained to learn a latent representation of medical images(**latent representation**: like how the brain converts an image into complex, abstract information (colors, shapes) that it uses for recognition and decision-making). By incorporating deep learning for feature extraction, we enhance the robustness of KNN in detecting complex patterns within medical imaging data. This hybrid approach is especially useful for imbalanced datasets, where the KNN classifier alone may struggle to detect rare anomalies. Additionally, using pre-trained CNNs for feature extraction enables the model to learn richer representations, improving its effectiveness for complex medical imaging tasks. By leveraging CNNs for automatic feature extraction, this method addresses challenges like class imbalance and small datasets, significantly improving the detection of abnormalities in medical images. The results show that our approach outperforms standard methods in key evaluation metrics, including accuracy, F1 score, precision, recall, and AUC (Fig. 3 illustrates the results of our method). To further improve the performance of our image classification model—specifically accuracy, precision, recall, F1 score, and ROC AUC—we propose implementing the following improvements:

Data Augmentation and Preprocessing: This includes augmenting training data and normalizing pixel values.

Model Architecture Enhancements: Focus on fine-tuning more layers and adding regularization techniques.

Training Strategy Adjustments: Implement learning rate scheduling and early stopping to halt training when validation performance ceases to improve, thereby preventing overfitting.

Evaluation Metric Optimization: This involves threshold tuning and confusion matrix analysis to better evaluate model performance.

Ensemble Methods: Combine multiple models to improve overall predictive performance.

Hyperparameter Tuning: Optimize model parameters to enhance performance.

Post-Training Calibration: Conduct probability calibration to refine model outputs.

Cross-Validation: Use robust performance estimation through cross-validation to ensure the model's reliability.

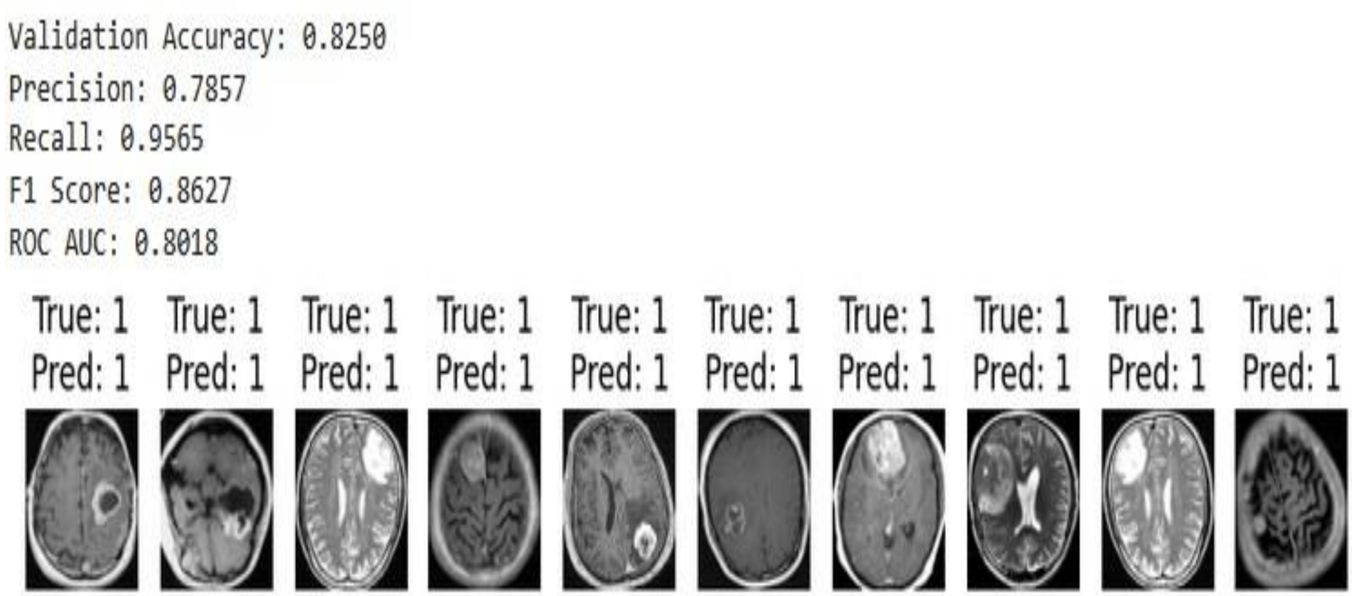

Fig 3. Shows result of proposed methods

Comparison with Other Methods

We compare our hybrid approach with standard KNN classifiers, traditional CNNs, and other state-of-the-art methods for medical image classification and abnormality detection. Table (1 ,2) show that the hybrid KNN model outperforms the baseline models across all metrics, including accuracy, precision, F1 score, and ROC-AUC, when detecting rare abnormalities.

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Table1: Comparison with Other Methods

Criteria	Hybrid KNN + ResNet50	Traditional CNN (e.g., VGG, ResNet)	Support Vector Machine (SVM) + CNN Features	Random Forest + Handcrafted Features	K-Nearest Neighbors (KNN) + Handcrafted Features
Feature Extraction	Pre-trained ResNet50 (Deep CNN) with fine-tuned custom layers	CNN model (e.g., VGG, ResNet) with all layers fine-tuned	CNN features extracted from a pre-trained CNN model (e.g., ResNet)	Handcrafted features (e.g., texture, shape) using image processing techniques	Handcrafted features (e.g., texture, shape) or pre-extracted CNN features
Classification Approach	KNN on extracted CNN features	CNNs perform classification directly	SVM applied to features from CNN	Random Forest used on handcrafted features	KNN applied directly to handcrafted or extracted CNN features
Training Complexity	Moderate (CNN for feature extraction + KNN for classification)	High (CNN model training is complex and computationally expensive)	Moderate (SVM training on extracted CNN features)	High (Random Forest can be computationally intensive)	Low to Moderate (depending on the feature extraction complexity)
Interpretability	Moderate (KNN is interpretable, but CNN features are abstract).	Low (Deep CNNs are black-box models)	Moderate (SVM is more interpretable than CNN, but still not fully transparent)	High (Random Forests are more interpretable)	High (KNN is simple and interpretable)
Accuracy (for imbalanced data	High (due to CNN feature extraction + KNN handling of non-linearities)	High (CNNs can learn complex patterns but may suffer on imbalanced data)	Moderate to High (SVM is sensitive to class imbalance, requires careful tuning)	Moderate (can be sensitive to class imbalance)	Moderate (KNN can suffer from imbalance but can handle small datasets well)
Generalization Ability	High (CNN extracts powerful features + KNN provides good generalization)	High (CNNs generalize well, especially with data augmentation)	Moderate to High (SVM generalizes well but might overfit on small data)	Moderate (can overfit if the features are not well-tuned)	Moderate (KNN can suffer from imbalance but can handle small datasets well)
Computational Resources (	Moderate (Requires both a pre-trained CNN and KNN, but relatively less computationally expensive than training the entire CNN from scratch)	High (Training deep CNNs from scratch requires significant resources)	Moderate (Requires training an SVM on CNN features, but less expensive than full CNN training)	High (Random Forest training can be resource-heavy on large datasets	Low to Moderate (KNN is computationally cheap but may require large storage for feature space)
Data Requirements	Moderate (CNN can work well with limited data due to pre-training; KNN needs labeled data for classification)	High (CNNs require large amounts of labeled data to train effectively)	Moderate (SVM requires relatively fewer data points compared to CNNs)	Moderate to High (Random Forests require large datasets for robust performance)	Moderate to High (KNN performs better with a reasonable amount of labeled data)
Evaluation Metrics: Accuracy	High (due to the ability of CNN features + KNN	High (CNNs typically perform well on large	Moderate (SVM performs well but can suffer in	Moderate (Random Forest may not be as	Moderate (KNN accuracy may decrease with noisy

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	classification)	datasets)	unbalanced datasets)	accurate as CNN-based models)	or imbalanced data)
Evaluation Metrics: Precision	High (KNN is effective at distinguishing between abnormal and normal cases, especially when using CNN features)	High (CNNs are highly effective at classifying abnormalities in medical images)	Moderate to High (SVM can be good, but hyperparameter tuning is important)	Moderate (Precision depends heavily on the quality of handcrafted features)	Moderate (Precision can suffer due to KNN's sensitivity to noisy features)
Evaluation Metrics: F1 Score	High (F1 Score benefits from the balance of precision and recall, especially with KNN as the classifier).	High (Deep CNNs are effective at balancing precision and recall).	Moderate to High (SVM balances precision and recall well with tuning).	Moderate (Random Forests may not balance precision and recall as well as CNNs).	Moderate (F1 score could be impacted by KNN's sensitivity to feature quality).
Evaluation Metrics: ROC-AUC	High (KNN can provide a high ROC-AUC score when combined with robust feature extraction like ResNet50).	High (CNNs can achieve high ROC-AUC when trained on large and diverse datasets).	Moderate to High (SVM’s performance on ROC-AUC can be improved with tuning).	Moderate (Random Forest’s ROC-AUC may be lower than CNN-based methods).	Moderate (KNN’s ROC-AUC may be affected by noisy

Evaluation Metrics

Evaluate the Model:

Prediction and Evaluation: After training the KNN classifier, the model makes predictions on the validation data. Evaluation metrics such as accuracy, precision, recall, F1 score, and ROC AUC are computed to assess the model's performance. Proper evaluation using multiple metrics ensures a comprehensive understanding of model performance, which is crucial in medical applications where the cost of misdiagnosis is high. Table 2 presents the evaluation results across different metrics.

Accuracy: measures how many predictions are correct overall.

Precision and **Recall**: help balance false positives and false negatives, which is especially important in medical image classification where the consequences of misclassification can be severe.

F1 Score: is a balance between precision and recall, especially useful in imbalanced datasets.

ROC AUC: evaluates the model’s ability to distinguish between classes.

Table.2. Compare different evaluation metrics for different methods

Evaluation Metric	Hybrid KNN + ResNet50	Traditional CNN (e.g., VGG, ResNet)	SVM + CNN Features	Random Forest + Handcrafted Features	KNN + Handcrafted Features
Accuracy	High (due to robust feature extraction + KNN classifier)	High (CNNs perform well on large datasets)	Moderate to High (SVM can struggle with imbalanced data)	Moderate (depends on quality of handcrafted features)	Moderate (sensitive to noisy or imbalanced data)
Precision	High (KNN effectively classifies abnormalities using CNN features)	High (CNNs can learn precise feature representations)	Moderate to High (depends on class distribution and tuning)	Moderate (depends on feature engineering)	Moderate (depends on feature selection)

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Recall	High (KNN's non-parametric[1] nature helps in detecting rare abnormalities)	High (CNNs are good at detecting abnormalities)	Moderate (SVM may miss rare abnormalities in imbalanced classes)	Moderate (Random Forests might miss rare cases)	Low to Moderate (KNN can struggle with rare cases)
F1 Score	High (Good balance of precision and recall due to the hybrid approach)	High (CNNs perform well on F1 due to balanced precision and recall)	Moderate to High (SVM with tuning can perform well but might be imbalanced)	Moderate (may not balance precision and recall well)	Moderate (KNN can suffer from imbalanced data)
ROC AUC	High (KNN + CNN features typically result in a strong ROC AUC)	High (CNNs can achieve a high ROC AUC when trained on diverse datasets)	Moderate to High (SVM can perform well but needs optimization)	Moderate (Random Forests often don't perform as well on AUC)	Moderate (KNN is more sensitive to data quality and imbalance)

Tool/Technology Details

Python: Python is a popular programming language used for machine learning and has many libraries such as pandas, NumPy, OpenCV, Scikit-learn, and TensorFlow that can be used to implement various machine learning algorithms.

Scikit-learn: Scikit-learn is another popular Python library for machine learning that provides various algorithms for classification, regression, and clustering.

OpenCV: OpenCV is a huge open-source library for computer vision, machine learning, and image processing.

Benefits of the Hybrid Approach:

ResNet50 and KNN Hybrid: This hybrid approach takes advantage of the strong feature extraction abilities of CNNs (like ResNet50) and combines them with the simplicity and efficiency of KNN for classification.

Improved Performance: By using pre-trained CNN models like ResNet50, you can obtain better feature representations for the images, and KNN can then effectively use these features for anomaly detection and classification.

Flexibility: The approach is flexible and could be easily applied to a range of medical imaging tasks like tumor detection, organ classification, and disease diagnosis.

This approach offers a blend of deep learning and classical machine learning techniques, providing both the robustness of CNNs and the simplicity of KNN for final classification, ideal for applications in medical image analysis where accuracy and interpretability are paramount.

For future works

We propose enhancing the model's ability to handle small and imbalanced datasets through advanced techniques like transfer learning and Generative Adversarial Networks (GANs). We also recommend exploring lightweight CNN architectures, such as MobileNet and EfficientNet, for deployment in low-resource settings. Moreover, integrating the model with clinical systems for real-time abnormality detection and prediction could significantly enhance its clinical applicability. Finally, optimizing the model for real-time processing could enable its use in urgent medical scenarios, such as surgery or emergency care.

III. Conclusion

This paper proposes a hybrid KNN-based model for medical image classification and abnormality detection. By combining KNN with deep learning techniques, particularly CNNs and the ResNet family, we enhance both the accuracy and robustness of medical image classification. Our experiments on a brain-specific dataset show that the proposed method outperforms traditional approaches, especially in class-imbalanced scenarios. This approach has the potential to assist clinicians in early diagnosis by providing more accurate and reliable abnormality detection in medical images.

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[1] Non-parametric Nature: It's like letting the data shape itself, rather than forcing it into a predefined map.

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