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Optimizing classification models for medical image diagnosis: a comparative analysis on multi-class datasets

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ABSTRACT

The surge in machine learning (ML) and artificial intelligence has revolutionized medical diagnosis, utilizing data from chest ct-scans, COVID-19, lung cancer, brain tumor, and alzheimer parkinson diseases. However, the intricate nature of medical data necessitates robust classification models. This study compares support vector machine (SVM), naïve Bayes, k-nearest neighbors (K-NN), artificial neural networks (ANN), and stochastic gradient descent on multi-class medical datasets, employing data collection, Canny image segmentation, hu-moment feature extraction, and oversampling/under-sampling for data balancing. Classification algorithms are assessed via 5-fold cross-validation for accuracy, precision, recall, and F-measure. Results indicate variable model performance depending on datasets and sampling strategies. SVM, K-NN, ANN, and SGD demonstrate superior performance on specific datasets, achieving accuracies between 0.49 to 0.57. Conversely, naïve Bayes exhibits limitations, achieving precision levels of 0.46 to 0.47 on certain datasets. The efficacy of oversampling and under-sampling techniques in improving classification accuracy varies inconsistently. These findings aid medical practitioners and researchers in selecting suitable models for diagnostic applications.

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1. INTRODUCTION

In the realm of medical diagnostics and patient care, the significance of accurate and timely disease detection cannot be overstated [1], [2]. One of the pivotal tools in modern medicine is medical imaging, particularly in the context of identifying diseases such as lung cancer, brain tumors, and chest abnormalities [3]–[5]. These life-threatening conditions, affecting millions worldwide, require early diagnosis for effective treatment and improved patient outcomes. Medical imaging not only aids in disease identification but also guides medical practitioners in formulating precise treatment plans [6], [7]. The quality of healthcare provided is significantly influenced by the robustness of the algorithms used in classifying and diagnosing these conditions [8]. It is within this context that this research is conducted.

Despite the advances in medical imaging and the availability of diverse datasets, the classification of medical images remains a challenging task [9]. A major challenge arises from the imbalanced distribution of data in multi-class medical datasets. The rare occurrence of certain diseases in comparison to others often leads to skewed class distributions, potentially affecting the performance of classification algorithms. The need to accurately diagnose and classify instances of lung cancer, brain tumors, and chest abnormalities has motivated this study. Furthermore, addressing the issue of class imbalance in medical datasets is crucial to ensure that classification algorithms provide reliable results.

The primary objective of this research is to conduct a comprehensive performance analysis of classification algorithms on an imbalanced multi-class medical dataset. The study aims to evaluate the suitability and effectiveness of various classification algorithms in diagnosing medical conditions based on medical images. The research endeavors to identify the strengths and weaknesses of these algorithms, with the ultimate goal of enhancing the accuracy and reliability of medical image classification.

This research seeks to answer the fundamental question of how different classification algorithms perform when applied to an imbalanced multi-class medical dataset encompassing lung cancer, brain tumors, and chest abnormalities [10], [11]. In addition to this central inquiry, it aims to unravel the strengths and weaknesses of individual algorithms support vector machine (SVM), machine learning (ML) in medicine: Performance calculation of dementia prediction by SVM, k-nearest neighbors (K-NN), artificial neural network (ANN), and stochastic gradient.

Descent (SGD) in the context of medical image classification, particularly addressing the challenges posed by imbalanced class distributions [12]–[19]. Furthermore, the research explores the potential of K-fold cross-validation with a value of 5 in mitigating class imbalance effects and enhancing algorithm performance. By addressing these research questions, this study endeavors to offer valuable insights into the performance of classification algorithms on imbalanced multi-class medical datasets, thus improving diagnostic accuracy and healthcare quality.

The following details the methodology of this study, including the data collection process, image segmentation techniques, feature extraction methods, and model evaluation metrics. The results will be analyzed for each algorithm, followed by interesting conclusions and future implications.

2. METHOD

To provide a systematic and structured approach, this research adopts the methodological framework illustrated in Figure 1. Figure 1 delineates the stages, starting from the collection of medical image data to the classification performance evaluation. Detailed explanations for each stage are presented in the following subsection.

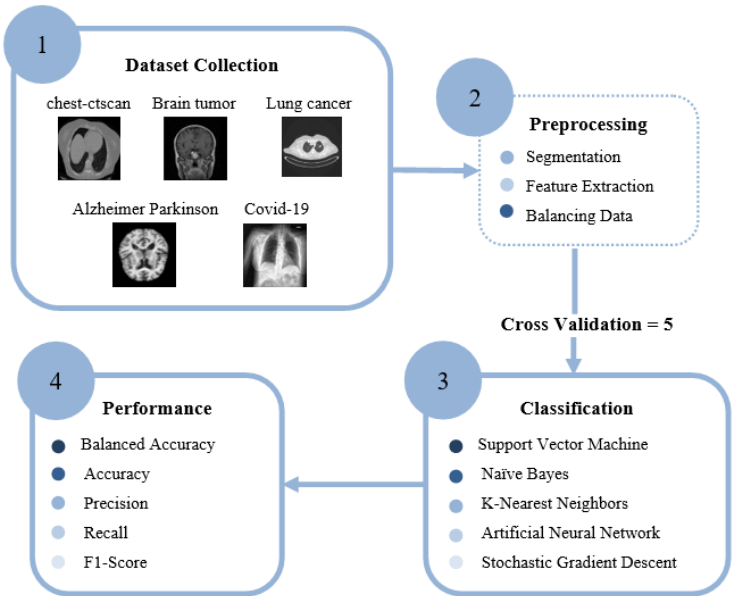


Figure 1. Visualization of the research methodology flowchart

2.1. Medical issue data collection

The study used five medical image datasets with multiclass categories taken from Kaggle.com, with varying number of classes. The Chest CT-Scan dataset has four classes with a total of 613 data, each of which has an imbalanced data distribution. The COVID-19 data set has three classes with 251 data in total, as well as with a imbalance in the distribution of data. The IQ-OTH/NCC-Lung Cancer dataset features three classes with a total of 1097 data points, similarly characterized by data distribution imbalance. Furthermore, the Brain Tumor Classification (MRI) dataset is composed of four classes, including a total of 2870 data points with an imbalanced data distribution. Finally, the Alzheimer's Parkinson diseases dataset consists of three classes with a total of 6477 data, and an imbalanced distribution of data. In addition, the research applied oversampling and undersampling to balance the data on all datasets [20]–[22]. This research begins with the data exploration stage to understand the characteristics of the image datasets used. Medical issue data collection involves visualization as well as statistical analysis to identify patterns, anomalies, and important information in data sets. General information on the datasets used in this study can be found in Table 1.

Table 1. Information datasets

Datasets	Number of cases	Number of attribute	Number Name of class	 Number in each class	Atribute characteristics	Missing value
Chest CT-Scan	613	7	4	195 115 148 155	Numeric	No
COVID-19	251	7	3	111 70 70	Numeric	No
IQ- OTH/N CC -Lung Cancer	1097	7	3	120 561 416	Numeric	No
Brain Tumor Classification (MRI)	2870	7	4	826 822 395 827	Numeric	No
Alzheimer Parkins on Diseases	6477	7	3	2561 3010 906	Numeric	No

2.2. Pre-processing data

This research involves several stages of preprocessing, namely, feature segmentation, feature extraction, and data balancing. Early stages in data preprocesing involve image segmentation using the Canny method [23]. This step aims to separate objects from the background on the image, improve data quality, and prepare them for the feature extract stage. The Canny algorithm belongs as a popular method in edge detection on image processing, involving several stages such as smoothing with Gaussian filters, gradient calculation, non-maximum suppression, and the application of thresholds to produce sharper edges [24]. The mathematical formula underlying this method is listed in (1).

$$E\,(x,y) = \sqrt{G_x\,(x,y)^2 + G_y\,(x,y)^2} \tag{1}$$

Here, $G_x\,(x,y)^2$ *and* $G_y(x,y)^2$ espectively are the gradients of the image in the horizontal and vertical directions. The results of image segmentation using the Canny method on medical datasets are shown in Figure 2.

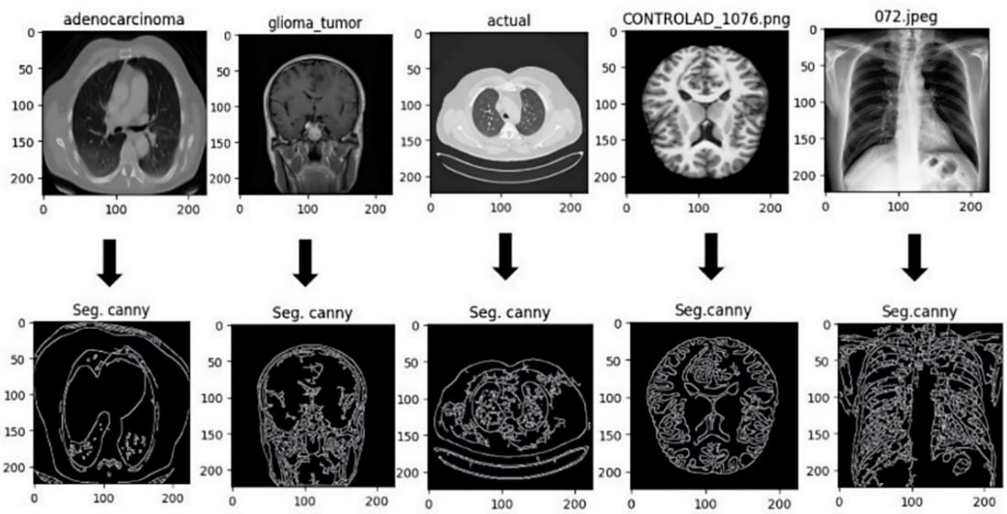


Figure 2. Image segmentation results canny medical datasets

After the segmentation process, the next stage is the extracting of features using the hu-moment method. Hu-moments is one of the methods used for extracting features of shapes or contours of objects in images. This feature has invarian properties to translation, rotation, and scaling, so it is suitable for use in shape recognition applications. The formula for calculating the center moment μ_{pq} can be seen in (2).

$$h_{ij} = \frac{M_{ij}}{M_{00}^{(i+j)/2+1}} \tag{2}$$

Where x_c and y_c are the mass center of the image, $p + q$ is the order of the moment, and $f(x, y)$ is the pixel value on the coordinate (x, y). Figure 3 shows a visualization of extracting humoment features using Scatter Plot and Heatmap on each dataset.

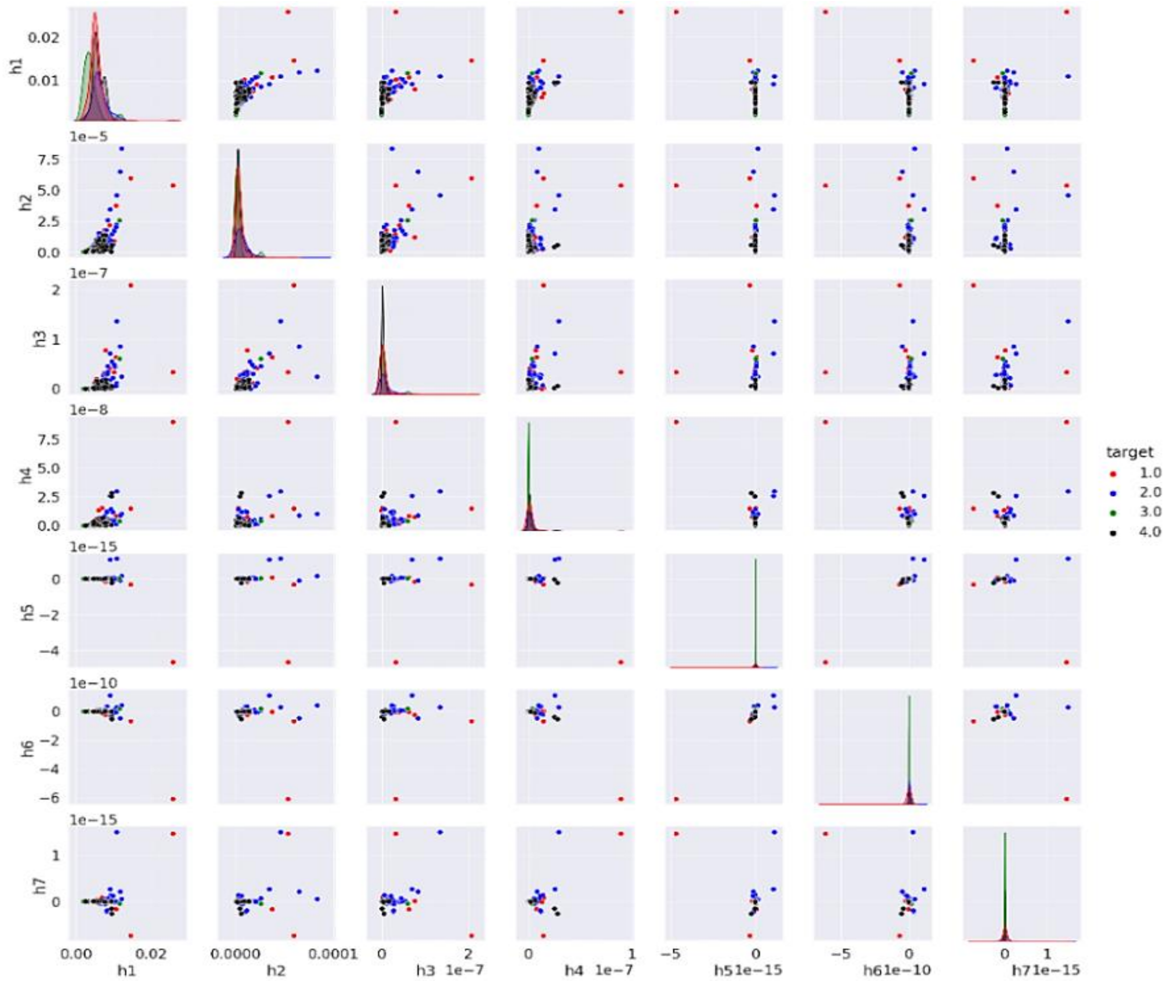
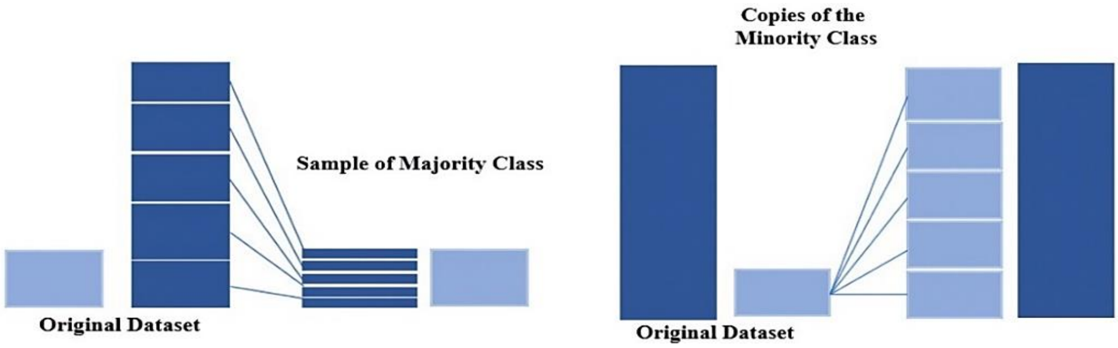


Figure 3. Plot scatter visualization output extraction feature: hu-moment on each chest ct-scan dataset

Resampling, a concept in data science, refers to efforts aimed at maintaining a balance in the distribution among different classes or labels within a dataset. This is particularly crucial in the context of classification or data analysis involving imbalanced classes. You can observe the data resampling visualization for under-sampling and over-sampling in Figure 4.

Under-sampling is a technique employed in machine learning to address class imbalance by reducing the number of samples from the majority class. Conversely, over-sampling involves increasing the number of samples in the minority class to achieve a balanced dataset. This balancing process is crucial to prevent the model from exhibiting bias towards the majority class or disregarding the minority class. As depicted in Table 2, implementing these strategies helps to mitigate potential biases and improve the model's overall performance.



(a) (b)

Figure 4. Data resampling visualization (a) Under-sampling and (b) Oversampling

Table 2. Data balancing

Balancing data in class	Datasets				
	CHEST CT-SCAN	COVID-19	IQ-OTH/NCC-lung cancer	Brain tumor classification	Alzheimer parkinson diseases
Oversampling	195	111	561	827	3010
	195	111	561	827	3010
	195	111	561	827	3010
	195				
Undersampling	115	70	120	395	906
	115	70	120	395	906
	115	70	120	395	906
	115				

2.3. Classification

Classification is used to identify specific patterns or characteristics within data that distinguish each class. By leveraging the information contained in the data, the classification function makes decisions regarding the most appropriate class for new objects that have not been classified before. The classification algorithms used in this study include SVM, naïve Bayes, K-NN, ANN, and SGD [25], [26].

SVM is a ML algorithm used for classification and regression tasks. The goal is to construct a hyperplane that has the maximum margin between different classes in the dataset [27]. The margin is the distance between the hyperplanes and the nearest points of each class. SVM can be used for both binary and multi-class classification problems. SVM can also be applied to multi-class classification problems using approaches such as one-versus- rest (OvR) or one-versus-one (OvO). Here is the basic SVM formula for the problem of multiclass classification with the OvR approach can be seen in (3).

$$y(x) = argmax_i(w_i \cdot x + b_i) \tag{3}$$

Where, $y(x)$ is the predicted class or label for x data, $argmax_i$ is the maximum argument operation, which produces the index i that produce the largest value among the calculated elements, w_i are the weight vectors associated with class i, x are the vectors of the input data that are to be forecast, b_i is the bias or shift associated to class i.

naïve Bayes is a probabilistic classification algorithm based on the Bayes theorem. This algorithm assumes that the features in the dataset are conditionally independent of the target class [28], [29]. Although these assumptions are very simple and may not always be true, naïve Bayes often provides good performance in many classification tasks, especially in the case of high-dimensional text and data. Naïve Bayes' basic formula for classification can be seen in (4).

$$P(C|X) = \frac{(P(X|C)P(C))}{P(X)} \tag{4}$$

Where, $P(C \mid X)$ is a posterior probability, a class C probability occurs on $X\ data,$ $P(X|C)$ is the probability of the likelihood, that is, the probability of the data X occurs if class C occurs, $P(C)$ was a prior probability that class C occurred without additional information, and $P(X)$ was the Probability of data X occurring, also called a normalization factor.

K-NN is a classification algorithm based on the distance between points in a feature space. To classify a sample, this algorithm searches for the nearest sample in the exercise data set and takes the majority of the class from those neighbours as a class prediction. The basic formula of K-NN for classification can be seen in (5).

$$y(x) = mode\ (\{y_i |\ x_i\ is\ a\ neighbor\ k(x)\}) \tag{5}$$

Where, $y(x)$ is the class prediction created for the input data x, y_i is a class of the i -neighbor of the x input data, x_i is the data neighbor of i of the data input x, $k(x)$ is the number of nearest neighbors to be used in the prediction for the x entry data, and $mode(.)$ refers to the most frequently appearing value in the assembly.

ANN is a computing model inspired by biological neural tissue. It consists of layers of artificial neurons that are interconnected [29]. Each neuron takes input, processes it, and gives its output to the next neuron. ANN can be used for a variety of tasks, including classification. The basic ANN formula for classification can be seen in (6).

$$y(x) = f(w \cdot x + b) \tag{6}$$

Where, $y(x)$ is the output or prediction generated by the model for input data x, $f(.)$ is the activation function, which transforms the input value into a more structured output, w is the weight vector that connects input x to output y, and b is the bias or shift added to the multiplication result $w \cdot x$.

SGD is an optimization algorithm used to train a machine learning model, including a classification model. This algority seeks a weight that minimizes a loss function through repeated iterations by updating the weight using the gradient of a cost function. The basic SGD formula for the problem of multiclass classification, in particular with the OvR approach, can be seen in (7).

$$w_{t+1} = w_t - \eta \cdot \nabla J_i(w_t) \tag{7}$$

Where, w_{t+1} is the weight vector that is updated on iteration $t + 1$, w_t is the weights vector on the current iterations (iteration t) η is the learning rate, which controls how much learning step is taken in each iterated, and $\nabla J_i(w_t)$ is the gradient of the $J_i(w)$ loss function against the w -weight vector in the training system i.

2.4. Evaluation matrics

Evaluating the performance of classification models heavily relies on evaluation metrics that provide a comprehensive perspective. One such metric is Balanced Accuracy, which combines True Positive Rate (accurate positive identification) and True Negative Rate (accurate negative identification), offering a balanced view between both classes [27], [30], [31]. Additionally, Accuracy measures overall predictions, while Precision emphasizes accurate positive identification. Recall, on the other hand, assesses the overall identification of positive cases. Likewise, F-measure, by harmonizing Precision and Recall, provides a holistic perspective. A strong understanding of these metrics is crucial for accurate interpretation and model enhancement. The equations for Balanced Accuracy, Accuracy, Precision, Recall, and F-measure can be found in (8) to (11).

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{8}$$

$$Pericision = \frac{TP}{(TP+FP)} \tag{9}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{10}$$

$$F - measure = \frac{2(presisi \times recall)}{(presisi+recall)} \tag{11}$$

3. RESULTS AND DISCUSSION

The research findings provide a comprehensive performance analysis of various machine learning algorithms on an imbalanced multi-class medical dataset. Three distinct scenarios, each employing a different data processing technique, were considered: no processing (Table 3), oversampling (Table 4), and undersampling (Table 5). Here, we present the results and discuss their implications.

Table 3 presents the performance results of ML algorithms on the original dataset before any processing. Notably, K-NN outperforms other algorithms across multiple metrics. It achieves the highest balanced accuracy of 0.53, accuracy of 0.57, precision weighted of 0.66, recall weighted of 0.57, and F1 weighted of 0.56. This suggests that K-NN is well-suited for classifying lung cancer, brain tumors, and chest abnormalities, showcasing its adaptability in a multi-class medical image classification context. On the other hand, algorithms like SVM and naïve Bayes lag behind in performance. This may be attributed to their limited ability to handle imbalanced datasets, resulting in suboptimal classification.

Table 3. Performance results before balancing the datasets

Σ Rata-rata	SVM	Naïve Bayes	K-NN	ANN	SGD
Balencend accuracy	0.43	0.44	0.53	0.52	0.52
Accuracy	0.52	0.47	0.57	0.56	0.56
Precision weighted	0.43	0.48	0.56	0.56	0.56
Recall weighted	0.52	0.47	0.57	0.56	0.56
F1 weighted	0.42	0.4	0.56	0.55	0.55

Table 4 shows the performance results after applying oversampling to the dataset. K-NN maintains its top position with the highest balanced accuracy (0.65), accuracy (0.65), and F1 weighted score (0.64). Oversampling has significantly improved the performance of all algorithms by addressing the class imbalance issue. K-NN effectively leverages the oversampled data to enhance its classification accuracy. While all algorithms benefit from oversampling, K-NN continues to excel, highlighting its adaptability to changes in dataset characteristics.

Table 4. Performance results after oversampling the datasets

Σ Rata-rata	SVM	Naïve Bayes	K-NN	ANN	SGD
Balencend accuracy	0.5	0.46	0.65	0.57	0.57
Accuracy	0.5	0.46	0.65	0.57	0.57
Precision weighted	0.45	0.45	0.66	0.57	0.57
Recall weighted	0.5	0.46	0.65	0.57	0.57
F1 weighted	0.42	0.39	0.64	0.56	0.56

Table 5 reveals the performance results after implementing undersampling. K-NN remains at the forefront with an accuracy of 0.55 and an F1 weighted score of 0.54. Notably, other algorithms, including SVM and naïve Bayes, show improvements compared to the original dataset, thanks to undersampling. Despite reducing the training data volume, undersampling enhances the overall performance of these algorithms. However, K-NN retains its superior performance, emphasizing its adaptability to different dataset characteristics.

Table 5. Performance results after undersampling the datasets

Σ Rata-rata	SVM	Naïve Bayes	K-NN	ANN	SGD
Balencend accuracy	0.49	0.46	0.55	0.55	0.55
Accuracy	0.49	0.46	0.55	0.55	0.55
Precision weighted	0.46	0.45	0.55	0.55	0.55
Recall weighted	0.49	0.46	0.55	0.55	0.55
F1 weighted	0.41	0.39	0.54	0.54	0.54

Overall, these results consistently position K-NN as the top-performing algorithm in various multi-class medical image classification scenarios, regardless of the data processing technique applied. Oversampling and undersampling techniques prove effective in addressing class imbalance and improving overall performance. While K-NN stands out as the most reliable choice, the findings contribute to our understanding of the impact of different data processing strategies in medical image analysis.

The findings of this research have significant practical implications for the healthcare sector, underscoring the importance of algorithm selection and data processing techniques in enhancing disease diagnosis and medical image analysis. However, it is important to note that the research findings are constrained by the use of a specific dataset, which may impact the generalizability of the results to other medical image datasets. Additionally, the utilization of oversampling and undersampling techniques may not entirely address the challenges posed by class imbalance. Therefore, it is recommended that future research explores more advanced oversampling and undersampling techniques or incorporates deep learning models for medical image analysis. Furthermore, expanding the research to encompass a diverse range of medical image datasets and integrating clinical validation will provide a more comprehensive understanding of algorithm performance in real-world healthcare settings.

4. CONCLUSION

In concluding this study, we have conducted a comprehensive examination of classification algorithms on a multi-class medical dataset marked by imbalances, specifically concentrating on lung cancer, brain tumors, and chest abnormalities. Our findings underscore the pivotal role of algorithm selection in the realm of medical image analysis, with K-NN consistently emerging as a robust performer, displaying the highest balanced accuracy and accuracy scores across diverse scenarios. This implies that K-NN may offer a more equitable trade-off between precision and recall, a crucial consideration in medical diagnostics. The outcomes of our research significantly contribute to the evolving knowledge landscape in medical image analysis, emphasizing the imperative of choosing appropriate algorithms for specific classification tasks. The practical implications are substantial, as the insights gained hold the potential to enhance the accuracy and reliability of disease diagnosis in the healthcare sector. However, it is imperative to acknowledge the study's limitations, particularly those associated with dataset-specific findings. We strongly recommend further research to explore advanced techniques and extend the investigation to encompass a variety of medical image datasets, ensuring robust and clinically validated results. This research serves as a foundational step for future endeavors aimed at elevating healthcare quality through the integration of advanced technology and machine learning.

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