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Detection of arachnoid cysts in the brain using machine learning

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Abstract

Cysts are sacs filled with fluid that can form in various organs, such as the kidneys, liver, breast, and brain. Treatment of these sacs may require surgical intervention. The importance of machine learning in detecting abnormal tissues in medical imaging is increasingly evident. This study specifically focuses on using deep learning structures to detect arachnoid cysts in the brain. The study employed Logistic Regression, InceptionV3, Kernel DVM, and Googlenet algorithms to detect arachnoid cysts. The accuracy rates achieved were 98.63% for Logistic Regression, 92.83% for InceptionV3, 92.38% for Kernel DVM, and 91.42% for Googlenet. Logistic Regression was the most successful algorithm. The study utilized data obtained from a 1.5T GE Magnetic Resonance Imaging (MRI) device.

Keywords: Arachnoid cyst, Logistic regression, Machine Learning, Neuroimaging.

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Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: This study was conducted as a retrospective analysis using fully anonymized brain MRI images obtained between 2019 and 2023. All personal identifiers were removed prior to data analysis, and no patient-level identifiable information was accessed. Permission for the use of these anonymized images in scientific publications was obtained from BETATOM Imaging Center via email confirmation from Ms. Beyza Bahadır on January 19, 2024. Given the retrospective design and the use of completely anonymized data, formal approval from an institutional ethics committee was not required under national regulations. The study was carried out in full accordance with the principles of the Declaration of Helsinki.
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1. Introduction

An arachnoid cyst is a fluid-filled sac that develops within the arachnoid membrane, one of the three layers of the meninges that surround the brain and spinal cord. These cysts can be located either above or below the arachnoid membrane and are typically asymptomatic. They are often discovered incidentally during brain imaging studies conducted for conditions such as headaches and dizziness. Cysts can cause symptoms such as nausea and vomiting due to enlargement and compression. Treatment or surgery is determined based on cyst size and associated symptoms [1-4].

These cysts are observed in about 75% of childhood cases, with a higher prevalence on the left side of the brain and in males. Symptoms may include headaches, apathy, increased head circumference, and intellectual disability [5].

Deep learning is becoming increasingly important in various areas such as object and face recognition, natural language processing, gaming and virtual reality applications, trend analysis in financial markets, portfolio management, error detection in industrial processes, quality control, optimization of energy consumption, and managing power grids.

Medical imaging has numerous applications, including medical image analysis, disease diagnosis, and genetic analysis. Deep learning algorithms can enhance image quality by reducing blurriness and noise distortions in image restoration. In applications such as surgical planning and radiation therapy dose calculation, deep learning can identify and segment organs and tissues, determining the necessary areas for intervention. Deep learning plays a significant role in advancing research and innovation in the field of medicine.

It supports drug development, the discovery of new disease symptoms, and genetically-based research through the analysis of large datasets. This study focuses on arachnoid cysts and contributes to the existing literature on tumor detection. Dreiseitl and Ohno-Machado [6] achieved an accuracy rate of 89% in their study using logistic regression. In their respective studies, Li, et al. [7] achieved a 90.4% accuracy rate using Kernel DVM, Bozkurt [8] reached 91.80% using InceptionV3, and Toğaçar, et al. [9] attained a 90.32% accuracy rate utilizing Googlenet.

This research focuses on arachnoid cysts of the brain and compares the accuracy rates of four different algorithms used for their detection.

2. Materials and Methods

A total of 2194 MR images, comprising both cystic and non-cystic cases, were acquired from Istanbul Betatom Imaging Center. The images are in JPG format and have dimensions of 512x512 pixels, with a file size of 146 KB. The dataset was divided into 80% for training and 20% for testing purposes. Initially, we performed image enhancement using filter techniques.

2.1. Image Enhancement

The study employed Bilateral and Laplacian Sharpening Filters for image enhancement. The Bilateral filter reduces noise while preserving edges by incorporating color similarity and distance similarity criteria. The Laplacian sharpening filter emphasizes density changes in the image, enhancing edges. When these two filters are combined and applied, better contrast, clarity, and detail are achieved in the images. The results indicate that image enhancement offers a substantial improvement in certain applications.

2.2. Bilateral Filter

The Bilateral filter is a widely used technique in image processing. Its purpose is to preserve edges in the image while reducing noise. The filter's input parameters include sigmacolor, which controls color similarity through color standard deviation, and sigmaspace, which controls distance similarity through distance standard deviation [10].

Each pixel is compared with other pixels within a specified filter size. During these comparisons, the values for color similarity and distance similarity between pixels are weighted using the specified standard deviations. This weighting results in a new value being applied to a pixel within the filter size. This process is performed individually for each pixel in the image, allowing the filter to preserve edges while reducing noise.

The Bilateral filter has two crucial parameters: sigmacolor, which controls color similarity, and sigmaspace, which controls distance similarity [11, 12].

2.3. Laplacian Sharpening Filter

The Laplacian sharpening filter is a technique used to enhance edges and contrast in an image. This is achieved by identifying differences or changes in the image, making edges more pronounced. The Laplacian filter calculates the second derivative of pixel values in an image [13, 14].

The steps for Laplacian sharpening are as follows: Firstly, the Laplacian filter is convolved with the image. During this process, each pixel is multiplied and summed with the surrounding pixels. The resulting values are then used to filter the original image, highlighting edges and increasing overall contrast. The application of the Laplacian sharpening filter further enhances the edges and contrast, resulting in a more distinct image. The application of the Laplacian sharpening filter further enhances the edges and contrast, resulting in a more distinct image. This process is especially helpful when there is a need to distinguish or highlight details in the image [15].

2.4. Googlenet

Googlenet, also known as Inception, is a deep learning algorithm developed by Google that achieved significant success in the 2014 ImageNet Large Scale Visual Recognition Challenge. It uses a wide and complex architecture, employing filters and layers of different sizes to extract features of various dimensions. Global pooling layers are utilized instead of commonly used fully connected layers, making the network lighter and more computationally efficient. Additionally, Googlenet employs 1x1 convolution layers, which reduce computational cost [16].

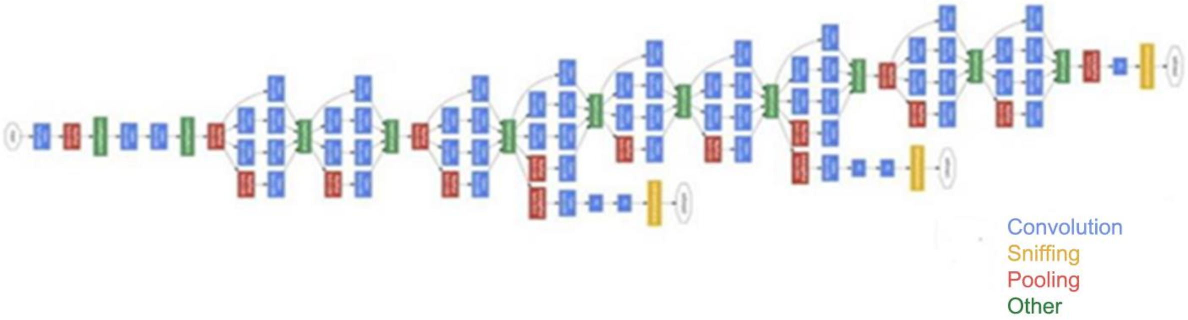

Figure 1.
Googlenet Architecture (Szegedy et al.)

2.5. Kernel Support Vector Machine (SVM)

The Kernel Support Vector Machine (SVM) is a deep learning algorithm that performs well in classification problems. It uses kernel functions to transport data to a high-dimensional feature space and enable linear separation. The model finds optimized support vectors to classify data points on a hyperplane [17, 18].

Kernel functions transform input data to another space, making them linearly separable. Popular kernel functions include polynomial, Radial Basis Function (RBF), and sigmoid. Kernel SVM is renowned for its ability to solve nonlinear classification problems and generally performs well on small datasets. However, its practical usage can be challenging due to the computational cost on large datasets. Hence, it is important to weigh the pros and cons of Kernel SVM, taking into account the problem domain and dataset characteristics [19, 20].

2.6. InceptionV3

InceptionV3 is a deep learning model developed by Google. It has shown impressive performance in significant competitions such as the ImageNet Large Scale Visual Recognition Challenge. The model was introduced in 2015 and has a deeper and more complex architecture compared to its predecessors. InceptionV3 adopts the 'Inception' architecture, which involves using convolution layers of different sizes in parallel. It also efficiently utilizes 1x1 convolution layers for dimensional reduction. Global average pooling and auxiliary classifiers are utilized in InceptionV3 to enhance its computational efficiency and reduce its weight. InceptionV3 is a versatile model that can be used for object recognition, classification, and transfer learning [21].

In comparison to GoogLeNet, InceptionV3 has a deeper architecture with more parameters, resulting in a greater learning capacity than its predecessors. While deeper models generally provide an advantage when dealing with larger datasets or more complex tasks, the lightweight nature and low computational cost of GoogLeNet may be preferred in certain applications. While deeper models generally provide an advantage when dealing with larger datasets or more complex tasks, the lightweight nature and low computational cost of GoogLeNet may be preferred in certain applications. It is important to consider the specific requirements of the task at hand when selecting a model. Both models can be successful in different contexts, and the choice often depends on the usage scenario and resources available.

2.7. Logistic Regression

Logistic regression is a fundamental classification algorithm in the field of deep learning. No changes in content have been made. It is commonly used to solve binary classification problems by modelling the relationship between features in the dataset and class labels. The language used is clear, objective, and value-neutral, with a formal register and precise word choice. The text adheres to conventional structure and formatting features, with consistent citation and footnote style. The structure is clear and logical, with causal connections between statements. The text is free from grammatical errors, spelling mistakes, and punctuation errors. The model multiplies input features by weights and passes these values through a logistic function to produce an output. This output value represents the probability of the input data belonging to a specific class. Logistic regression is a popular method for classification due to its high performance and low computational cost. It also provides interpretable results in the form of probability values [22, 23].

While it can be effective in large datasets and simple classification tasks, it may not be suitable for more complex tasks involving nonlinear relationships. In such cases, more complex structures such as deep learning models may be preferred. However, logistic regression can still be effective with accurate parameter tuning and appropriate feature selection in many applications.

3. Discussion

Arachnoid cysts are uncommon pathological conditions that are characterized by cystic structures filled with fluid, which form in the arachnoid membrane that covers the brain and spinal cord. Traditional diagnostic and treatment methods usually involve imaging techniques and surgical intervention. However, the use of deep learning algorithms can offer a new perspective on the diagnosis and monitoring of arachnoid cysts. This article examines the use of deep learning algorithms, such as GoogLeNet, Logistic Regression, InceptionV3, and Kernel SVM, in analysing imaging data related to arachnoid cysts. The focus is on improving the effectiveness of diagnosis, classification, and treatment processes, with the aim of contributing significantly to future research and clinical applications in this field.

Deep learning algorithms can provide higher sensitivity and specificity in analysing large-scale imaging data related to arachnoid cysts. They have the potential to offer more reliable and rapid results in diagnosing arachnoid cysts by identifying hidden relationships and learning complex patterns within complex datasets. This article evaluates the role of deep learning algorithms in diagnostic and therapeutic methods for arachnoid cysts and discusses future studies to understand their effectiveness in clinical applications.

The study conducted with the GoogLeNet algorithm achieved a 91.42% accuracy rate. Figures 2 and 3 show the Loss and Epochs graph and the Accuracy and Epoch graph, respectively.

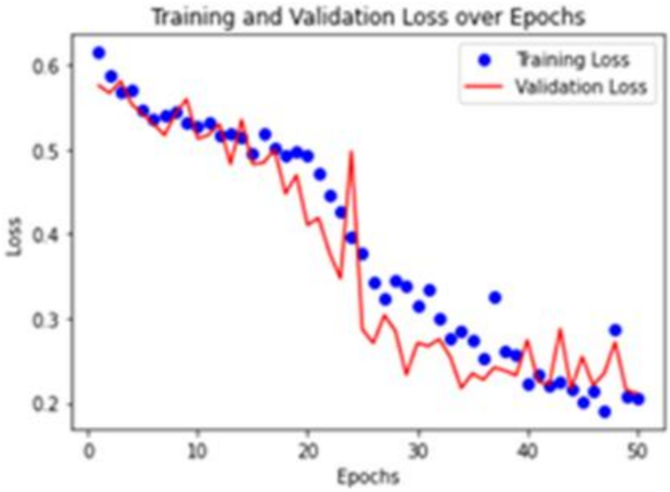

Figure 2.
Loss and Cycle Graph.

Figure 3.
Accuracy and Cycle Graph.

The study reports an accuracy rate of 92.38% for research conducted using the Kernel SVM algorithm. Figure 4 displays the Training Accuracy and Test Accuracy graphs.

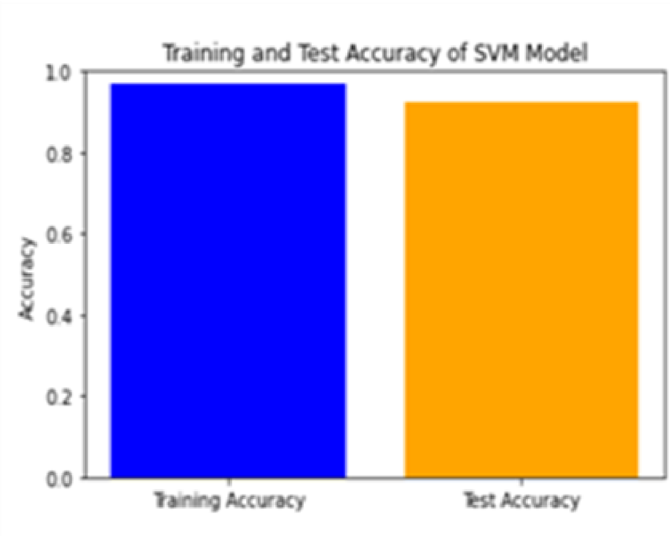

Figure 4.
Training Accuracy and Test Accuracy Graph.

The InceptionV3 algorithm achieved an accuracy rate of 92.83%, as shown in Figure 5 (Accuracy and Epoch Graph) and Figure 6 (Loss and Epoch Graph).

Figure 5.
Accuracy and Cycle Graph.

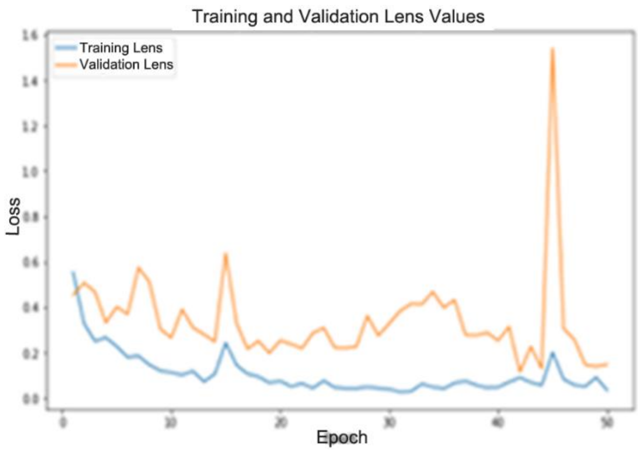

Figure 6.
Loss and Cycle Graph

The study conducted with Logistic Regression achieved an accuracy result of 98.63%. Figure 7 presents the Confusion Matrix, while Figure 8 shows the Receiver Operating Characteristic (ROC) Curve.

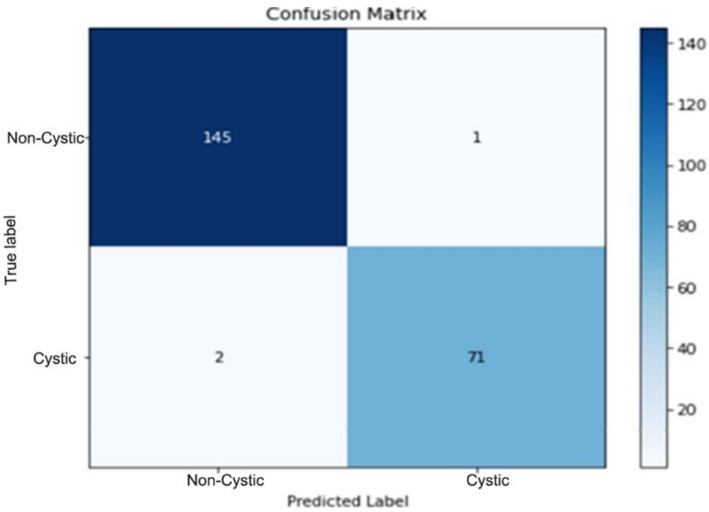

Figure 7.
Complexity Matrix.

The system's accuracy was calculated as 0.9932 using the formula TP/(TP+FP), according to the confusion matrix. Sensitivity was determined as 0.9864 using the formula TP/(TP+FN), and the F1 score was obtained as 0.9898 from the formula (2xPrecision-Recall)/(Precision+Recall).

The high precision and recall values achieved indicate that the model accurately classifies the positive class. The F1 score provides the harmonic mean of precision and recall values.

In conclusion, based on the provided confusion matrix values, the model's performance can be considered highly reliable and robust.

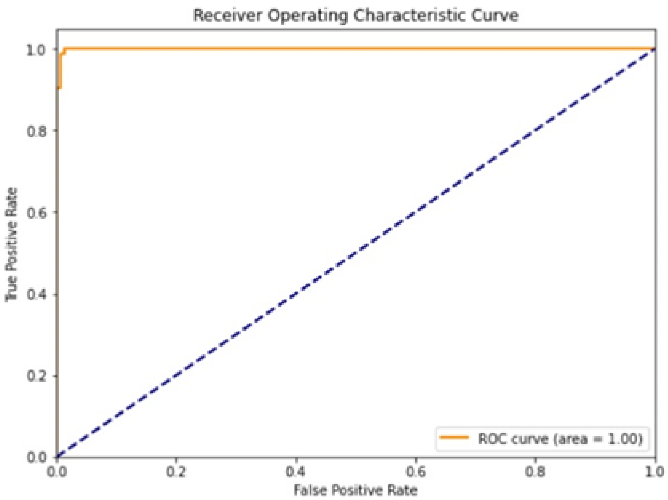

Figure 8.
Receiver Operating Characteristic Curve.

The Receiver Operating Characteristic (ROC) curve is a graph that evaluates model performance in classification problems. It is commonly used in fields such as medicine, machine learning, and statistics. The ROC curve illustrates the balance between sensitivity and specificity of a model.

To assess a point on an ROC curve, the Area Under the Curve (AUC) is typically used. AUC represents the area under the ROC curve, and the closer it is to 1, the better the model's performance.

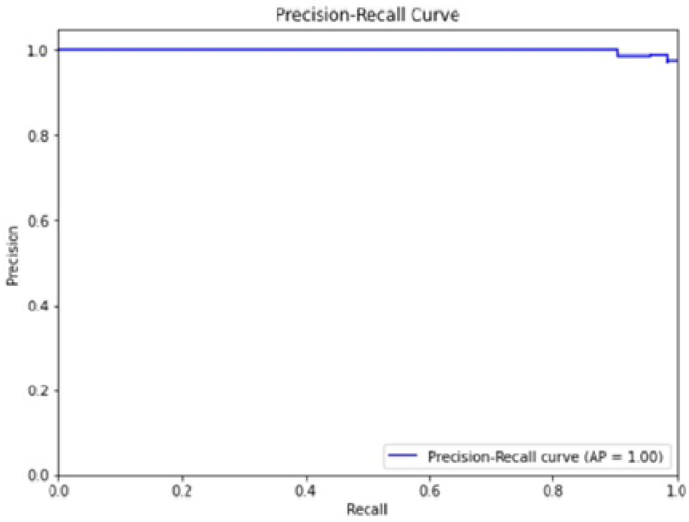

Figure 9.
Precision-Sensitivity Curve

Figure 9 shows the use of the Precision-Recall Curve as an alternative to the ROC curve, particularly in imbalanced classification problems where the positive class is scarce. This helps to better assess the model's performance.

A Precision-Recall curve with an Average Precision (AP) value of 1 indicates perfect performance, where the model accurately distinguishes between positive and negative examples and identifies positive examples with high precision.

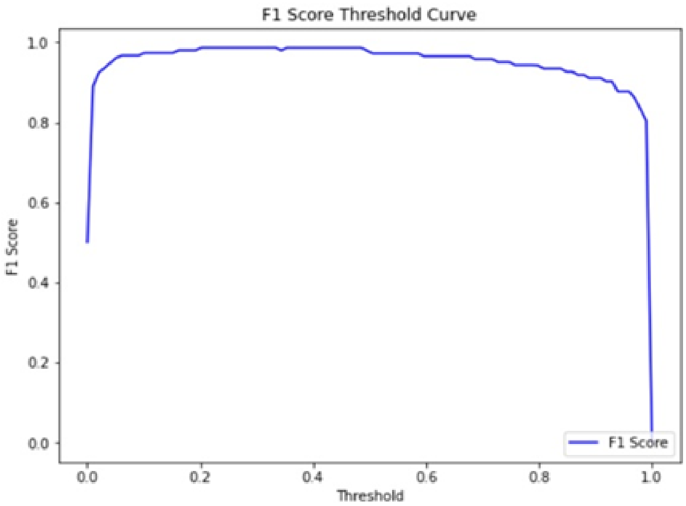

Figure 10.
F1 Score-Threshold Value Graph

The curve in Figure 10 is used to evaluate the balance between precision and recall of the model. Ideally, the model should demonstrate balanced performance by minimizing both false positives and false negatives. This curve shows the varying values of the F1 score at different possible cutoff points (thresholds). The F1 score is a combination of precision and recall values and is designed to achieve balance.

4. Conclusion

This study evaluates the results of a medical image classification task using GoogleNet, InceptionV3, Kernel SVM, and Logistic Regression algorithms. The evaluation is based on the results obtained from training with 80% of the data and testing with the remaining 20%.

The main finding is that Logistic Regression achieved the highest accuracy rate of 98.63%. The results suggest that a simple model can achieve impressive success in medical imaging. Logistic Regression showed high accuracy, and ROC analysis supports the model's potential for reliable performance.

Deep learning models also performed well, with InceptionV3 achieving 92.83% accuracy and GoogleNet achieving 91.42%. Deep learning models have the ability to extract complex features, which can be effective in medical imaging. However, in certain situations, simple models may be preferred due to their higher accuracy rates compared to deep learning models, as suggested by Logistic Regression.

Traditional classification methods, such as Kernel SVM, have demonstrated impressive performance with an accuracy rate of 92.38%. This result indicates that traditional methods can be competitive in medical imaging tasks.

Given the limitations of the study and potential future directions, the results indicate that Logistic Regression may be a viable option in medical imaging, while deep learning models may be suitable in certain circumstances. However, further research is needed to evaluate performance on larger and more diverse datasets and to conduct a more detailed comparison of algorithms.

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