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A Comparative Study for Evaluating the Performance of Various Classification Techniques on Brain Tumour

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ABSTRACT

Image processing methods have become consistently used approaches in a wide variety of applications with modern technology devices. Image classification and segmentation is a common topic in computer vision as well as a backbone and focal point in image processing approaches. Biometric and biomedical image processing are two of the most common examples of image processing applications that we have seen over the past two decades. in medicine, there is a great need for modern imaging technology algorithms that can be used to detect the internal organs of the human body in the process of disease diagnosis. To this end, researchers are working every day to develop new methods or improve existing methods that will help in efforts to improve human life and health. in this study, a comparative study was conducted to evaluate the performance of different types of machine learning classification algorithms on brain tumor images. According to the result obtained, the performance of the models differs in the accuracy of their classification capabilities. Different performance measurements are used during the evaluation and interpretation of the results and the results obtained are presented in the comparison table in the results section. Six classification models are used, which are mainly used in the field of Machine Learning (ML) and Artificial Intelligence (AI). Future studies may increase the comparison techniques by adding other classification and clustering techniques to study the effectiveness of each technique in the classification operation of medical images.

Çeşitli Sınıflandırma Tekniklerinin Beyin Tümörü Görüntüleri Üzerindeki Performansının Değerlendirilmesine Yönelik Karşılaştırmalı Bir Çalışma

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ÖZ

Görüntü işleme yöntemleri, modern teknoloji cihazlarıyla çok çeşitli uygulamalarda sürekli olarak kullanılan yaklaşımlar haline gelmiştir. Görüntü sınıflandırma ve segmentasyon, görüntü işleme yaklaşımlarında omurga ve odak noktasının yanı sıra bilgisayar görüşünde de yaygın bir konudur. Biyometrik ve biyomedikal görüntü işleme, son yirmi yılda gördüğümüz görüntü işleme uygulamalarının en yaygın örneklerinden ikisidir. Tıpta, hastalık teşhisi sürecinde insan vücudunun iç organlarını tespit etmek için kullanılabilecek modern görüntüleme teknolojisi algoritmalarına büyük ihtiyaç vardır. Bu çalışmada, farklı türdeki makine öğrenimi sınıflandırma algoritmalarının beyin tümörü görüntüleri üzerindeki performansını değerlendirmek için karşılaştırmalı bir araştırma yapılmıştır. Elde edilen sonuca göre, modellerin performansı sınıflandırma yeteneklerinin doğruluğunda farklılık gösterilmiştir. Sonuçların değerlendirilmesi ve yorumlanması sırasında farklı performans ölçümleri kullanılmıştır ve elde edilen sonuçlar, sonuçlar bölümündeki karşılaştırma tablosunda sunulmuştur. Esas olarak Makine öğrenmesi ve Yapay Zekâ alanlarında kullanılan altı sınıflandırma modeli kullanılmaktadır. Gelecekteki çalışmalar, her bir tekniğin tıbbi görüntülerin sınıflandırma operasyonundaki etkinliğini incelemek için başka sınıflandırma ve kümeleme teknikleri ekleyerek karşılaştırma tekniklerini artırabilir. Bu amaçla araştırmacılar, insanın yaşamını ve sağlığını iyileştirme çabalarına yardımcı olacak yeni yöntemler geliştirmek veya mevcut yöntemleri iyileştirmek için her geçen gün çalışmaktadır.

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INTRODUCTION

Image processing methods have become consistently huge in a wide variety of utilizations with modern methods and instruments. Image segmentation is a common topic in image processing, as well as a hotspot and focal point in image processing approaches (Zaitoun, 2015). Biometric and biomedical image processing are two of the most common image processing applications we've seen in the previous two decades (Wiley, 2018). The human visual system experiences an enormous arrangement of biometric qualities that permit them to identify biomedical images without conscious exertion. It is complex to provide this capacity to a machine (Al-Quraishi, 2021). Biometric ID systems are valuable in different applications like medical, commercial, and law enforcement applications. Criminal identities, security, video telephony, credit card verification, and photo IDs for identity are some of the most common real-world applications in the topic we're discussing. Recognition of human faces, fingerprints, signatures and a variety of other biometric images is a major area of study in image processing and computer vision. Likewise, numerous forms of biomedical non-evasive imaging modalities are utilized in the medical field for disease diagnosis and treatment planning, such as x-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound images, and numerous others. Internal architecture and dynamic physiological functions are mirrored in these imaging modalities. Understanding the main imaging modalities as well as the processing techniques used to enhance, filter, segment, and analyze such images is critical. The radiation in assorted structures used in these imaging procedures cooperates with different tissues to create images from which the physical and underlying data of different organs are removed (Wiley, 2018).

Image segmentation is a technique for partitioning an image into sub-component sections that are astonishingly homogeneous in feature, allowing some relevant information to be extracted. In image analysis, image segmentation occupies an important place (I. Journal, 2022). In a variety of applications, medical picture segmentation is critical in computer-aided diagnosis systems. classifying clinical images is fundamental In an assortment of uses including PC-supported analysis frameworks (CADS). Clinical imaging modalities like microscopy, ultrasound, dermoscopy, X-beam, CT, MRI, and positron outflow tomography (PET) have seen a lot of progression and improvement, which urges investigation to do novel clinical image analyzing methods (Al-Quraishi, 2021). The most essential medical imaging methodology, Image partition, remove the region of interest (ROI) by a self-loader or programmed process. It isolates a picture into segments in light of a depiction, for instance, dividing human organs/tissues for limited location, disease discovery/division, and mass identification in med applications. In this way, segmentation splits the image into relevant sections, clustering algorithms can be utilized to professionally separate the ROI from the backdrop by extracting the image's global features. K-means clustering, hierarchical clustering (HC), divisive clustering (DC), and mean-shift clustering (MSHC) are examples of clustering algorithms. Furthermore, because most medical images have irregular and fuzzy borders, fuzzy set and neutrosophic set theories become significant in the classification process to handle ambiguity in the medical images (Zaitoun, 2015).

Using available technologies, many experts have investigated numerous automated segmentation systems. Traditional technologies like detection filters and mathematical modeling were used in previous systems. Then, for a long time, machine learning approaches to extracting hand-crafted characteristics became the dominating strategy. The complexity of these systems has been deemed a significant barrier for their deployment and designing and extracting these elements has always been the primary focus for establishing such a system. A hybrid technique was used to detect a brain tumor from MR images was carried out by Kumar et al, (Kumar S., 2017). This hybrid approach utilizes the discrete wavelet transform (DWT) to extract features, a genetic algorithm to reduce the number of features, and a support vector machine (SVM) to classify brain tumors. Another CNN engineering for brain tumor growth order of three cancer types is available as Badža and Barjaktarović (M.M. Badža, 2020) presented in their study. The created network was tried utilizing T1 weighted differentiation MRI not set in stone to be more strong than previous pre-prepared networks. The network's performance was assessed using four methods: two databases and a mixture of two 10-fold cross-validation procedures. Hesamian et al. (M.M. Badža, 2020) researched deep-learning approaches for medical image segmentation and gave a significant assessment of common deep-learning techniques for medical image segmentation methods. The researchers investigated the most commonly used network topologies for medical picture segmentation and emphasized their advantages over their predecessors.

Davamani et al (Davamani, 2021) have shown a review on Biomedical Image Segmentation utilizing Deep Learning Methods. It discusses how various human medical defects can be diagnosed and treated. It is stressed that it is crucial for biomedical image segmentation, such as the detection of skin cancer, lung cancer, brain tumors, and skin psoriasis. Xiangbin Liu et al., (Liu, 2021) presented a deep learning-based medical image segmentation study. In a complete review, the authors emphasized convolutional neural networks (CNN) and their core ideas, capabilities, and performance in medical imaging, as well as medical image segmentation, approaches based on deep learning to help tackle the existing difficulties. Yahya Alzahrani et al. (Alzahrani Y. B., 2021) investigated the most widely used medical segmentation methods for practically all types of medical images. They categorized the methods and then compared, contrasted, and emphasized their primary benefits and drawbacks. Parish Shafi Dar and Devanand Padha, (Deshpande, 2022) did a review on Medical Image Segmentation, the review were extending the significant spot of images segmentation in dynamic data extraction and thinking upon flow procedures which are utilized in clinical imaging and talking about different headways in this exploration field. The correlation of new division procedures with prior strategies has been reported in Aganj et al. (2018). Further developing exactness, accuracy, the decreased time intricacy of division calculations, and a decrease in how much manual cooperation are recommended as future work. A technique to biological picture segmentation based on deep learning was studied in Haque and Neubert, (I. Rizwan, 2020). The fundamentals of deep learning methods are researched, as well as an overview of successful picture segmentation implementations for various medical applications. Some research challenges are noted, as well as the need for future advancements. Unsupervised image division given the neighborhood focal point of mass was examined by Aganj et al. (2018). They proposed a proficient technique to bunch the pixels of a one-layered sign, which we then, at that point, use in iterative approaches for two-and three-layered image divisions. They acquainted another methodology with solo image division in light of the computation of the neighborhood focus of mass and investigated a productive strategy to bunch the pixels of a one-layered sign, which we then, at that point, use in an iterative calculation for two-and three-layered picture division. High-level prior-based loss functions for medical picture image segmentation were investigated by El Jurdi et al. (2021). We focus on a high-level prior incorporated at the loss function level in this survey. The approaches are classified based on the prior's nature: object shape, size, topology, and inter-region constraints. Wang et al. (2018) investigated interactive medical image segmentation with image-specific fine-tuning using deep learning. By merging CNNs into a bounding box and scribble-based segmentation pipeline, they present a unique deep learning-based interactive segmentation framework. The three-dimensional divisions of the cerebrum cancer center and entire mind growth from various MR successions were just the cancer center in one MR grouping was commented on for preparing, and 2-D division of numerous organs from fetal attractive reverberation (MR) cuts, where just two kinds of these organs were donated for preparing.

In the last years many researchers in the field of medical imaging and soft computing have made significant advances in the field of brain tumor segmentation. Traditional machine learning models are generally mathematical algorithms such as linear regression trained based on manually organized features. The major advantage of using a supervised formulation is that supervised methods can perform different tasks by simply changing the training set. Audited methods have the potential to reduce the manual engineering task by providing labeled data, appropriate features, and appropriate parameters for the learning algorithm.

MATERIALS AND METHODS

Classification Algorithms

Classıficatıon is an undertaking that requires the use of the ML approach to figure out how to allocate class labels to occasions from the domain of the issue. Ordering inbox messages as "spam" or "not spam" is a straightforward illustration of classification. health, education, and business are only a couple of models. It's a grouping-based system that is applied in a wide scope of ventures. In AI, there are numerous particular kinds of arrangement issues that may be confronted, and everyone requires an alternate displaying strategy. The adequacy of different AI grouping models on brain tumor pictures was examined in this performance (Wang, 2018).

Decision Trees (DTs)

Decision Trees (DTs) are one more kind of ML approach used to take care of classifications and regressions issues. By gaining straightforward decision principles surmised from past information, the reason for applying a DTs is to foster a preparation model that can be utilized to anticipate the class or worth of the objective variable (training data). The DTs area famous strategy in AI and are regularly utilized in tasks research, explicitly in the decision analysis, to assist with deciding the best technique for accomplishing an objective. We start from the base of the tree while utilizing Decision Trees to figure class labels for a record (Belgiu, 2016).

A set of given data X=x_1, x_2, x_3,......, x_N, and answers Y=y_1, y_2, y_3, ..., y_N. Here it is chosen irregular examples from the training set and fit trees to them on different occasions. The DTs for the variables x_i and y_i are f(x_i,y_i). At long last, we might average the results of the relative multitude of trees fi that compares to x' to estimate the outcomes for x' (in case of continuous).

$$\widehat{f} = \frac{1}{N}\sum_{i=1}^{N} f_i \ (X') \tag{1}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(f_i(X') - \hat{f})}{N-1}} \tag{2}$$

Random Forest (RF) Classifier

Random forest (RF) is a Supervised ML Algorithm that is utilized commonly in Classification and Regression issues. It gathers choice trees on different models and takes their bigger part vote for the course of action and typical on account of relapse. One of the primary components of the RF Algorithm is that it can manage the enlightening record containing ceaseless elements under relapse and downright factors because of arrangement. It performs better results for arrangement issues (Belgiu, 2016).

K-Nearest Neighbors (KNN)

The supervised AI algorithm k-nearest neighbors (KNN) is a straightforward, simple-to-execute method that might be utilized to address both classification and regression issues. Model: Let's say there is an image of an animal that resembles a feline or a canine, yet we need to realize whether it's a cat or a dog. We can involve the KNN technique for this recognizable proof since it depends on a likeness measure. The NN model will search for similitudes between the new informational index and the cat and dog photographs, and sort it as either a cat or a dog in light of the most comparative ascribes (Ertuğrul, 2017). The nearest NN type classifier is the one closest neighbor classifier that relegates a Direct X toward the class of its nearest neighbor in the element space, that is:-

$$C_n^{1nn}(x) = Y_{(1)} \tag{3}$$

The KNN classifier can be seen as appointing the k closest neighbors a weight 1/k and all others 0 weight $w_{ni}.with\ \sum_{i=1}^{n} w_{ni} = 1$ This can be summed up to weighted closest neighbor classifiers. That is the place where the ith closest neighbor is allotted a weight An undifferentiated from the result on the solid consistency of weighted closest neighbor classifiers likewise holds.

$$R_R\,(C_n^{wnn}) - R_R\,(C^{Bayes}) = (B_1 s_n^2 + B_2 t_n^2)\{1 + 0(1)\} \tag{4}$$

$for\ constants\ B_1\ and\ B_2\ where$

$$s_n^2 = \sum_{i=1}^{n} w_{ni}\ and\ t_n = n^{-2}/_d \sum_{i=1}^{n} w_{ni} \left\{i^{1+\frac{2}{d}} - (i-1)^{1+\frac{2}{d}}\right\}. \tag{5}$$

The optimal waiting scheme $\{w_{ni}^*\}_{i=1}^{n}$, that adjusts the two things in the showcase above, is given as streams: set,

$$k^* = [Bn^{\frac{4}{d+4}}, \tag{6}$$

$$w_n^* = \frac{1}{k^*}\left[\, 1 + \frac{d}{2} - \frac{d}{2k^{*2/d}}\left\{i^{1+2/d} - (i-1)^{1+2/d}\right\}\right] \tag{7}$$

for $i = 1,2,\dots,k^*$ and $w_{ni}^* = 0$ for $i = k^* + 1,\dots,n$.

Support Vector Machine (SVM)

The SVM classifier depends on the rule of finding the greatest edge hyperplane that best separates the two classes (for instance, sick and healthy). The classifier is prepared using only support vectors (i.e. examples that put two parallel hyperplanes for optimum). Each data piece is represented as a point in n-dimensional space in the SVM algorithm, with the value of each property being the value of particular coordinates in Fig1. The classification is then completed by identifying the exaggeration that clearly distinguishes the two categories. Because data points are mixed in non-linear SVM, it is difficult to separate training instances using a linear line (Fig1 and Fig2). At this time, we must apply the kernel approach to alter the data in such a way that separation is achievable. Choosing the kernel function, among other things, can have a big impact on the SVM model's performance. However, there is no way to know which kernel is optimum for a particular pattern recognition problem. Trial and error is the only way to find the best kernel. We can start with a simple SVM and then try out various standard kernel functions. One kernel may be superior to the others, depending on the nature of the situation. In a statistically rigorous manner, an optimal kernel function can be chosen from a fixed collection of kernels (Kumar, 2017).

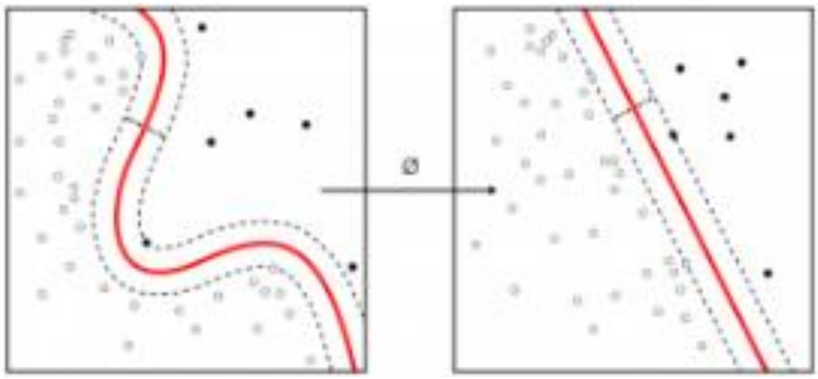


Fig.1. *Non-linear SVM* **Fig**.2. *Linear SVM*

Formulas,

$$y = a * x + b \tag{8}$$

$$a * x + b - y = 0 \tag{9}$$

Let vector X=(x,y) and W=(a,-1) then in vector from hyperplane is

$$W.X + b = 0 \tag{10}$$

Logistic Regression

Logistic regression (LR) is a quantifiable assessment method to expect a twofold outcome, for instance, yes or no, given a prior view of an enlightening collection. The LR model investigates the connection between at least one existing autonomous factor to foresee a reliant data variable. In the field of AI, strategic relapse has turned into a significant strategy. It empowers AI algorithms to group approaching information utilizing historical information (Sperandei, 2014).

$$P = \frac{1}{1 + e^{\gamma}(x - \mu)} \tag{11}$$

$$P(c|X) = P(x_1|c) \times P(x_2|c) \ldots \ldots \times P(x_n|c) \times P(c) \tag{12}$$

where μ and 1/λ are location and scale parameters, respectively. We may define the "fit" to y_i at a given x_i as:

Naive Bayes Classifier

It is a technique for classification given Bayes' Theorem and the presumption of indicator freedom. A Naive Bayes classifier (NBC), in basic terms, sets that the presence of one component in a class is inconsequential to the presence of some other element. The NBC model is easy to build and is particularly great for immense informational indexes. Other than straightforwardness, NBC is known to beat even incredibly complex order techniques. NBC has numerous applications, for example, Real-time estimating, Multi-class determining, Text grouping, Spam Filtering, Sensitivity Analysis, and Recommendation frameworks (Granik, 2017). Bayes' hypothesis gives an approach to working out the back likelihood of P(c|x) from P(c), P(x), and P(x|c). Look at equations 13 and 14 below:-

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)} \quad (13)$$

$$(c|X) = P(x_1|c) \times P(x_2|c) \ldots \ldots \times P(x_n|c) \times P(c) \quad (14)$$

P(c|x) :posterior probability (c, target) given predictor (x, attributes).

P(c): the prior probability of c.

P(x|c) is the probability which is the likelihood of the indicator given class..

P(x) is the earlier likelihood of the indicator.

Preprocessing Filters

One of the essential preprocessing steps in image processing filtering. Filtering is a fundamental strategy used to feature the elements or work on the nature of the image. A few fundamental tasks like edge identification, image enhancement, honing, and fixing in picture processing are performed utilizing some filtering operations activities. Channels help visual understanding of pictures and can be utilized for working with resulting computerized handling steps. Median channel (MF) was utilized in this study. The MF is a fundamental nonlinear channel that is utilized to eliminate commotion from an image. The MF first sorts all the pixel esteems in the rising request rundown and afterward computes the pixel esteem as the middle by taking the worth in the rundown. There are two principal benefits to utilizing the middle channel. The first is that it is not difficult to apply. The second is that it could be utilized to eliminate various sorts of clamor (Suhas, 2017).

Dataset

A Brain Tumor is considered as one of the forceful sicknesses, among youngsters and grown-ups. Cerebrum tumors represent 85 to 90 percent of all essential Central Nervous System(CNS) tumors. Consistently, around 11,700 individuals are determined to have cerebrum cancer (Brain MRI segmentation, January 31, 2022). The 5-year endurance rate for individuals with a harmful mind or CNS tumor is around 34% for men and 36 percent for ladies. Pituitary Tumors are named: Benign Tumor, Malignant Tumor, Pituitary Tumor, and so forth Legitimate treatment, arranging, and precise diagnostics ought to be executed to further develop the future of the patients. The best method to recognize cerebrum tumors is Magnetic Resonance Imaging (MRI). An enormous measure of image information is produced via the scans in Fig 3. These pictures are inspected by the radiologist. A manual assessment can be blunder inclined because of the degree of intricacies associated with cerebrum growths and their properties.

The entire set of 110 patients was split into 22 non-overlapping subsets of 5 patientseach. This was done for evaluation with cross-validation.

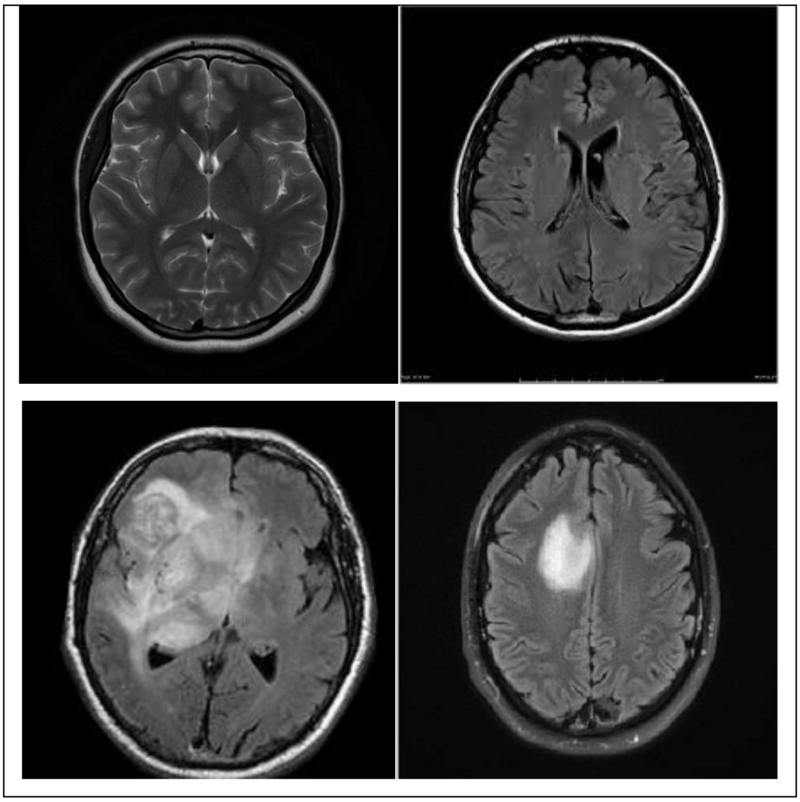


Fig 3. *The brain Tumor images (*Brain MRI, 2022)

Performance Metrics

In the study, there are a few measurements used to assess the performance of the classifier. Classification accuracy (CA) is the most generally involved measurement in many ML and AI models. Accuracy in an arrangement is characterized as the proportion of the quantity of accurately classified examples to the total number of information. The CA calculation formula was shown in Eq.(15).

$$Accuracy = \frac{Number\ of\ correctly\ classified\ data}{total\ number\ of\ data} \tag{15}$$

Classification accuracy (CA) is a viable measure to portray performance if the test dataset contains an equivalent number of tests from each class is marked and adjusted. Nonetheless, when working with a lopsided dataset, the framework ought to be assessed with more performance measurements. In this context, confusion matrices (CM) are considered for evaluating the data in different ways. Generally, the CM gives binary (true and false) classifications in table format. The CM contains values for four potential results: At the point when a certain data is correctly classified as positive, the CM is called true positive (TP). At the point when a certain data is incorrectly classified as negative, The type of CM will be false negative (FN). At the point when a certain data is classified correctly as negative, The type of CM will be true negative (TN). At the point when a certain data is classified incorrectly as positive, the type of CM will be negative (FP). With these values acquired from the CM, different metrics are calculated to express the performance of the classifier. Recall (sensitivity) that is computed from these outcomes is demonstrated in Eq. 16. Recall identifies the capability of the classification to expose true positives.

$$recall = \frac{TP}{TP + FN} \tag{16}$$

Precision is measured and computed as expressed in Eq. 17. Precision denotes the capability of the classification to avoid false positives.

$$Precision = 2 * \frac{TP}{TP + FP} \tag{17}$$

The F1 score used to explain the equilibrium among recall and precision is the symphonious mean of these two measurements. The F1 score is determined as computed in Eq. (18).

$$F1\ score = 2 * \frac{Precision * recall}{Precision + recall} \tag{18}$$

For each model used in this study, recall, precision, and F1 score values were interpreted along with the CA parameter.

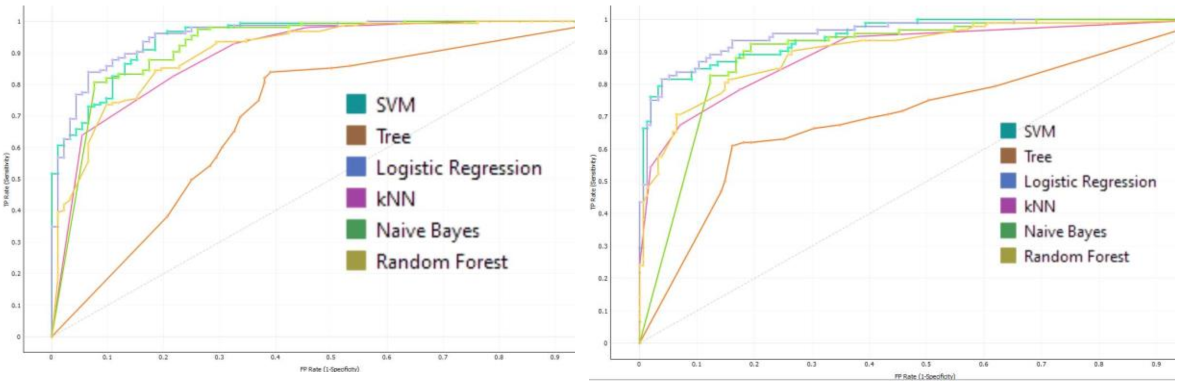
RESULTS AND DISCUSSION

The experimental methods of the approaches performed in the study are given in this segment. Different ML classification strategies have been tried. These classifications are the most remarkable and broadly utilized techniques that can without much of a stretch arrange complex information and label the dataset adequately. Six approaches were utilized in the review and tried their execution utilizing images from the Brain Tumor dataset (Brain MRI segmentation, January 31, 2022). This dataset contains 255 brain tumor images, a big part of the dataset is utilized for training images and the other half for test images. The size of these pictures is 481x321 or 321x481 pixels.

The results obtained in the research are shown in the table below using the above model evaluation methods. As can be seen, different achievements have been achieved for each method. However, the ROC curve graph is also shown in Figure 4, to carry out more interpretation about the success of each on brain dataset used in the study.

Table 1. *Comparison of classification models used in the study*

	AUC	**AC**	**F1**	**Precession**	**Recall**
SVM	0.9484	0.8988	0.8973	0.8998	0.8987
Logistic regression	0.9453	0.8866	0.8863	0.8863	0.8866
Naive Bayes	0.9236	0.8481	0.8398	0.8454	0.8381
KNN	0.8972	0.8359	0.8292	0.8357	0.8345
Random Forest	0.90463	0.82591	0.8261	0.8263	0.8259
Decision Tree	0.7036	0.7449	0.7427	0.7417	0.7449



a. The result of the images is classified as yes. **a.** The result of the images classified as no

Fig .4. *The brain Tumor images classification*

When Table 1 is examined, the highest coefficients in AUC, AC, F1, Precession and Recall values, respectively, were obtained in SVM. When the ROC curves in Figure 4 are examined, SVM and Logistic regression show very close values.

Classification of medical images is one of the most interesting research topics in the field of image processing and computer vision. The researchers are trying to provide models that can accurately classify these images to facilitate the diagnostic process in healthcare systems that can help doctors easily analyze images taken using imaging technologies such as MRI, CT, ultrasound, and son. this comparative research is carried out as a performance comparison of different types of machine learning classifications in brain tumor images. According to the result obtained, the performance of the models differs in the accuracy of their classification capabilities. During the evaluation and interpretation of the results, different performance measurements were used and the found result is presented in the comparison table in the results section. As shown in the study, 6 classification models are used, which are mainly used in the field of ML and AI. Future studies may use and enlarge comparison techniques by mixing classification and clustering techniques to study the effectiveness of each technique in the classification operation of medical images.

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GENİŞLETİLMİŞ ÖZET

Giriş

Son yıllarda tıbbi görüntüleme ve yumuşak hesaplama alanındaki birçok araştırmacı, beyin tümörü segmentasyonu alanında önemli ilerlemeler kaydetti. Geleneksel makine öğrenimi modelleri genellikle manuel olarak organize edilmiş özelliklere dayalı olarak eğitilmiş doğrusal regresyon gibi matematiksel algoritmalardır. Denetimli bir formülasyon kullanmanın en büyük avantajı, denetimli yöntemlerin yalnızca eğitim setini değiştirerek farklı görevleri yerine getirebilmesidir. Denetlenmiş yöntemler, öğrenme algoritması için etiketlenmiş veriler, uygun özellikler ve uygun parametreler sağlayarak manuel mühendislik görevini azaltma potansiyeline sahiptir.

Materyal ve Metot

Çalışmada gerçekleştirilen yaklaşımların deneysel yöntemleri bu bölümde verilmiştir. Farklı ML sınıflandırma stratejileri denenmiştir. Bu sınıflandırmalar, karmaşık bilgileri çok fazla zorlamadan düzenleyebilen ve veri kümesini yeterince etiketleyebilen en dikkat çekici ve yaygın olarak kullanılan tekniklerdir. İncelemede altı yaklaşım kullanılmış ve Beyin Tümörü veri setinden alınan görüntüler kullanılarak uygulanmaları denenmiştir. Bu veri seti 255 beyin tümörü görüntüsünü içerir, veri setinin büyük bir kısmı eğitim görüntüleri için, diğer yarısı ise test görüntüleri için kullanılır. Bu resimlerin boyutu 481x321 veya 321x481 pikseldir.

Bulgular

Bu çalışmada, farklı türdeki makine öğrenimi sınıflandırma algoritmalarının beyin tümörü görüntüleri üzerindeki performansını değerlendirmek için karşılaştırmalı bir araştırma yapılmıştır. Elde edilen sonuca göre, modellerin performansı sınıflandırma yeteneklerinin doğruluğunda farklılık gösterilmiştir. Sonuçların değerlendirilmesi ve yorumlanması sırasında farklı performans ölçümleri kullanılmıştır ve elde edilen sonuçlar, sonuçlar bölümündeki karşılaştırma tablosunda sunulmuştur. Esas olarak Makine öğrenmesi ve Yapay Zekâ alanlarında kullanılan altı sınıflandırma modeli kullanılmaktadır. Gelecekteki çalışmalar, her bir tekniğin tıbbi görüntülerin sınıflandırma operasyonundaki etkinliğini incelemek için başka sınıflandırma ve kümeleme teknikleri ekleyerek karşılaştırma tekniklerini artırabilir. Bu amaçla araştırmacılar, insanın yaşamını ve sağlığını iyileştirme çabalarına yardımcı olacak yeni yöntemler geliştirmek veya mevcut yöntemleri iyileştirmek için her geçen gün çalışmaktadır.,

Tartışma

Tıbbi görüntülerin sınıflandırılması, görüntü işleme ve bilgisayarla görme alanındaki en ilginç araştırma konularından biridir. Araştırmacılar, doktorların MRI, CT, ultrason ve oğul gibi görüntüleme teknolojilerini kullanarak alınan görüntüleri kolayca analiz etmelerine yardımcı olabilecek sağlık sistemlerinde tanı sürecini kolaylaştırmak için bu görüntüleri doğru bir şekilde sınıflandırabilen modeller sağlamaya çalışıyor. Bu karşılaştırmalı araştırma, beyin tümörü görüntülerinde farklı türde makine öğrenimi sınıflandırmalarının performans karşılaştırması olarak yürütülmektedir. Elde edilen sonuca göre modellerin performansları, sınıflandırma yeteneklerinin doğruluğunda farklılık göstermektedir. Sonuçların değerlendirilmesi ve yorumlanması sırasında farklı performans ölçümleri kullanılmış ve bulunan sonuç sonuçlar bölümünde karşılaştırma tablosunda sunulmuştur.