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Disease Classification of CXR Images by AlexNet Transfer Learning

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Abstract

The purpose of this study is to classify COVID-19 CXR(Chest X-Ray) images using a CNN(Convolutional Neural Network) modified from AlexNet using a transfer learning method so that it can be used as an auxiliary method when diagnosing diseases in medical settings. The Dataset used in the experiment uses "COVIDGR-1.0 Dataset". "COVIDGR-1.0 Dataset" is a collection of 784 anonymized X-ray images and, in collaboration with a team of radiologists, built into the dataset in accordance with labeling protocols.

The proposed CNN is a fine-tuned build of pre-trained AlexNet, which takes the "COVIDGR-1.0 dataset" as input and categorizes it into Normal, Mild, Moderate and Sever according to the labels and categories. Experimental results of the disease classification of CXR images show that the AUC(Area Under the Curve) is 0.8781, with accuracy of 87.81%.

It is believed that the results of this study can be used in the following fields. First, it can be used as an auxiliary tool for diagnosing lung diseases. Second, if the data set is ready, it can be used to classify other diseases. Third, data can be stored separately through classification. Fourth, in the medical field, the object to be classified can be imaged using a smartphone and then classified and stored.

This study has the following limitations. The problem with automatically classifying diseases is the vastness and integrity of the dataset. If the data is not prepared, it will cause problems with the accuracy of classification. And in the medical field, doctors' decision-making (diagnosis) is not limited to image data. There is a limitation in that doctors make decisions based on comprehensive data and that medical decisions cannot be made by machines without the doctor's intervention. Determining the decision threshold in decision making problems by AI is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts but of experts in the field. Therefore, medical staff in the field must participate in the process of developing AI in the medical field.

Future tasks include continuing research in connection with program input stage development, performance improvement, app development, and medical big data servers.

Key word: COVID-19 Chest X-Ray, CNN, Disease Classification, Confusion Matrix, AUC

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I. Introduction

The importance of early diagnosis and appropriate treatment for lung disease, which is considered a serious health problem, is being emphasized, and the development of deep learning (DL) technology is providing innovative solutions for this. Chest X-Ray(CXR) devices are installed in most medical institutions and mobile devices are also available, CXR imaging has become an important tool to determine whether lung disease has progressed due to infection. The "COVIDGR-1.0 Dataset" was used as the dataset for the study[1]. This is a dataset built by Spanish radiologists to support COVID-19 diagnosis. DL is achieving high results in many fields such as image classification and object detection. Convolutional Neural Network(CNN) is a DL model that extracts and classifies image features and has recently been actively used in the imaging field.The purpose of this study is to classify the disease grade of COVID-19 CXR images into normal, mild, moderate, and severe using a transfer learning method using Alexnet, a type of CNN.

II. Materials and Methods

1. Dataset for research

The dataset used for learning in the study was "COVIDGR-1.0 Dataset". "COVIDGR-1.0 Dataset" was constructed as a dataset by collecting 784 anonymized X-ray images in close collaboration with a team of radiologists at "Hospital Universitario San Cecilio" in Spain and following a strict labeling protocol. The collected 784 images were classified into 431 negative cases and 353 positive cases. Positive images are images of patients who tested positive for COVID-19 through Reverse Transcription Polymerase Chain Reaction(RT-PCR) within up to 24 hours between the X-ray image and the test. All images were taken with the same type of equipment and in the same format, and only posterior-anterior imaging (P-A projection) was considered. Images were categorized as normal, mild, moderate, and severe [1]. The figure below shows some of the images in the dataset by disease grade.

2. CNN

CNN models are a type of artificial neural network used in DL to evaluate visual information, and these networks can handle a wide range of tasks related to images, sound, text, video, and other media. CNN was created in the late 1990s by Professor Yann Lecunn at Bell Labs. CNN models have input layers, output layers, hidden layers, and millions of parameters, allowing them to learn complex objects and patterns. A convolution and pooling process is used to sample a given input before applying an activation function, where all inputs are partially connected to hidden layers and the fully connected layer at the end is the output layer. The output format itself is the same as the size of the input image. Convolution is a process that combines two functions to generate the output of another function, and the input image is changed by applying a filter to the CNN model. The CNN model was proposed to solve the problems of training time, network size, and number of variables. The CNN model combines the convolution and pooling parts that extract features and the extracted features, it is divided into classification parts[2]. Figure 1 shows the concept of the CNN model.

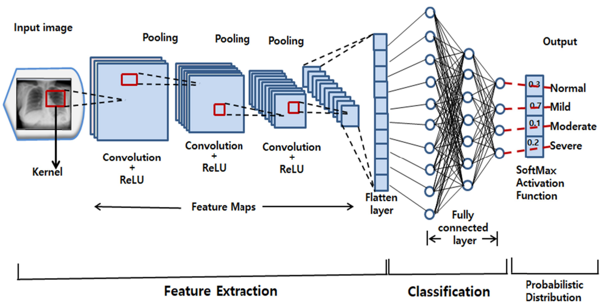


Figure 1. The concept of the CNN model

3. AlexNet

AlexNet is a CNN-structured Neural Network(NN) that won the ILSVRC (imageNet large scale visual recognition challenge) competition held in 2012[3]. The official paper is "ImageNet Classification with Deep Convolutional Neural Network"[4]. It is called AlexNet, named after the first author of the paper, Alex Khrizevsky, and AlexNet brought CNN to the spotlight again. AlexNet was designed as shown in Figure 2 with two GPUs in parallel structure to perform parallel computation[4].

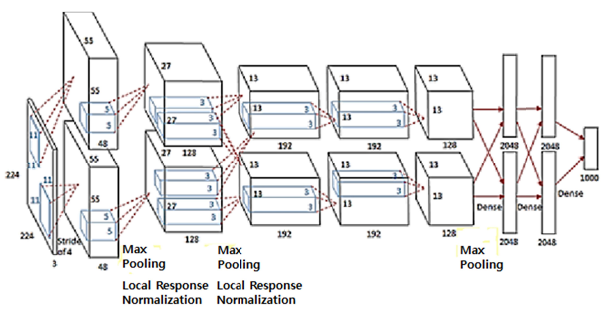


Figure 2. AlexNet with two GPUs in parallel

architecture to perform parallel computations.

4. Transfer learning of AlexNet

AlexNet receives "COVIDGR-1.0 Dataset" as input and outputs the probabilities of labels and categories in the image. Transfer learning is widely used in DL applications[5]. A pre-trained neural network can be used as a starting point for learning new tasks. Fine-tuning a neural network with transfer learning is usually much faster and easier than training the network from scratch using randomly initialized weights. Learned features can be quickly transferred to a new task using a smaller number of training images, and the transfer learning process of AlexNet is shown in Figure 3[6].

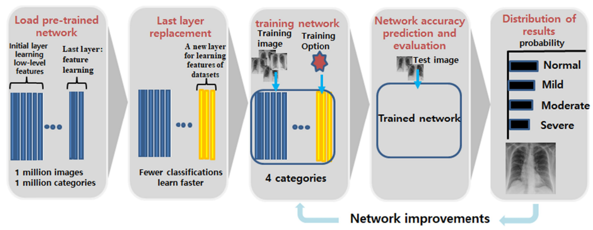


Figure 3. The transfer learning process of AlexNet

III. Experiment and Results

AlexNet CNN was modified and programmed using the transfer learning method to classify the grade of lung disease in CXR images of "COVIDGR-1.0 Dataset" into normal, mild, moderate, and severe. The experiment used MatLab R2023B on a computer equipped with a GPU. The experimental procedure was performed as shown in Figure 4.

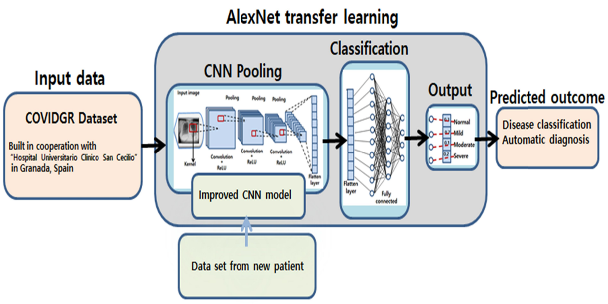


Figure 4. The experimental procedure

Unzipped the COVIDGR_Dataset.zip file and loaded it into the data storage. The images were labeled based on the folder name and the data was saved as an ImageDatastore object. Data stored in the computer was divided into training datasets and validation datasets. The splitEachLabel function is a function that splits the data storage into two new data storages and stores them. The split data was divided into 70% training data and 30% validation data. Sample images were displayed using the algorithm below, with 4 images in rows and 4 images in columns, a total of 16 images, as shown in Figure 5. The displayed image was converted from an RGB image to a gray image through a Matlab function, and the normalized image was displayed.

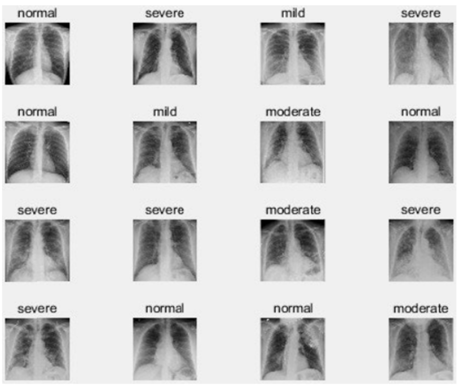


Figure 5. Sample images display

Finally, the verification image was classified using the classify function. The classification images with four disease names are shown in Figure 6 along with the predicted labeling.

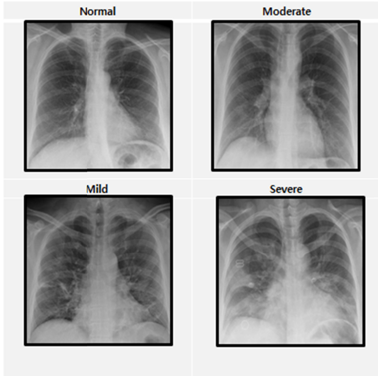
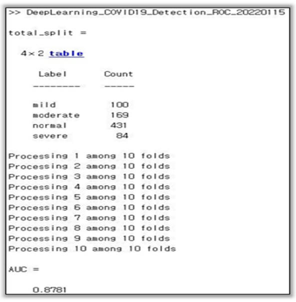


Figure 6. The classification images

Accuracy refers to the percentage of labels that a NN predicts correctly. The experimental results showed an accuracy of 87.8%, as shown in Figure 7.



```
>> DeepLearning_COVID19_Detection_ROC_20220115

total_split =

  4×2 table

     Label        Count
    --------      -----

    mild           100
    moderate       169
    normal         431
    severe          84

Processing 1 among 10 folds
Processing 2 among 10 folds
Processing 3 among 10 folds
Processing 4 among 10 folds
Processing 5 among 10 folds
Processing 6 among 10 folds
Processing 7 among 10 folds
Processing 8 among 10 folds
Processing 9 among 10 folds
Processing 10 among 10 folds

AUC =

    0.8781
```

Figure 7. Experimental result accuracy.

Figure 8 is a confusion matrix for evaluating the effectiveness of the CNN model. We can find out the accuracy and error rate of training through this confusion matrix.

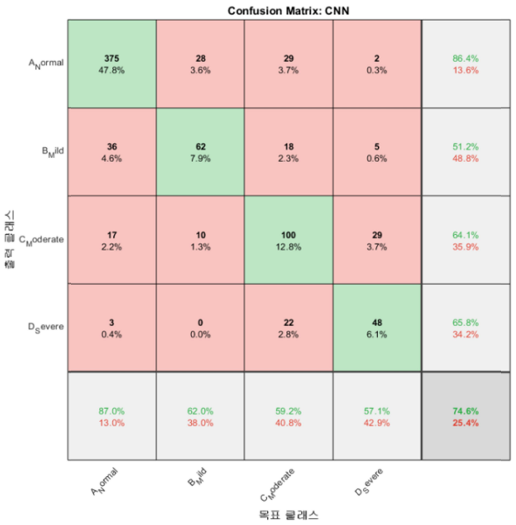


Figure 8. A confusion matrix for evaluating the effectiveness of the CNN model.

In the confusion matrix, as shown in <Table 1>, the accuracy was 74.0% and the error rate was 26.0%.

<Table 1> Accuracy and error rate

Accuracy	74.6%
Error rate	25.4%

To evaluate the performance of the CNN built for the study, precision, recall, and F1-Score are shown in <Table 2> for each disease classification.

<Table 2> Precision, Recall, F1-Score by classified disease

Evaluation items / Classification	Precision	Recall	F1-Score
Normal	87%	86%	43%
Mild	62%	51%	27.98%
Moderate	59%	64%	30.70%
Severe	57%	66%	30.59%

In this study, through experiments, ROC was obtained as shown in Figure 9 below. In the graph, the x-axis represents the false positive rate (FPR), and the y-axis represents the true positive rate (TPR), that is, the decision rate. The area of the x-axis in the ROC graph is called the area under the curve (AUC), and here it is found to correspond to 87.81% of the total area, as shown in Figure 7.

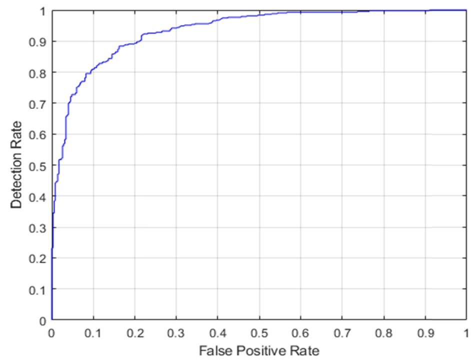


Figure 9. ROC graph

IV. Discussion

Classifying medical imaging diseases is being studied in the form of Computer Aided Diagnosis(CADx)[7]. Since the COVID-19 pandemic, many attempts have been made to detect CXR images by CNN. <Table 3> shows CNN-related research for detecting disease in COVID-19 chest X-ray images. The results from the paper described in <Table 3> are as follows. Ahmed Abdelgawad, et al.

(2020) proposed a CNN model to detect COVID-19 patients in chest X-ray images. This model was evaluated through a comparative analysis of two other CNN models. The proposed model performed with an accuracy of 97.56% and a precision of 95.34%. This model resulted in a receiver operating characteristic (ROC) curve area of 0.976 and an F1-score of 97.61. It was stated that this result could be further improved by increasing the dataset for model training[8]. Appasami S. Nickolas (2022) proposed a deep learning-based CNN model to detect COVID-19 in CXR. CXR collected data from various sources to train with augmentation and evaluate models widely used for COVID-19 detection and diagnosis. A Deep Convolutional Neural Network (DCNN)-based model was proposed for COVID-19 analysis with data augmentation. This model used the patient's CXR for COVID-19 diagnosis to help support doctors' diagnostic process in high workload conditions. The overall accuracy of COVID-19 classification was achieved at 93% by selecting the optimizer[9]. Zohreh Mousavi (2022) and others reported that on the test set, the proposed network achieved over 90% accuracy (i.e., Healthy against COVID-19 against the virus) for all scenarios except scenario V. An accuracy of 99% was achieved for separating COVID-19 in the Healthy group. The results showed that the proposed network is robust to noise up to 1 dB. It is worth noting that the proposed network also achieved over 90% accuracy for two additional databases that were only used as test databases. They also claimed that compared to state-of-the-art pneumonia detection approaches, the final results obtained from the proposed network are very promising[10]. Nigam et al. (2021) used VGG16, DenseNet121, Xception, NASNet, and EfficientNet on a dataset consisting of 16,634 images. This dataset is slightly larger than COVIDx8B, but unfortunately the authors have not released it publicly. The accuracy obtained with EfficientNetB7 was the highest at 93.48%[11]. Ismael and şengür (2021) used ResNet18, ResNet50, ResNet101, VGG16, and VGG19 for deep feature extraction and support vector machine (SVM) for CXR image classification. The highest accuracy was 94.7% obtained with ResNet50. However, they used a small dataset with only 380 CXR images[12].

<Table 3> CNN-related research for disease detection in COVID-19 CXR

Author	Journal (Year of publication)	Title	Accuracy
Ahmed Abdelgawad, Fatin Farhan Haque, Khandaker Foysal Haque, Lisa Gandy	**IEEE (2022)**	**Automatic Detection of COVID-19 from Chest X-ray Images with Convolutional Neural Networks**	97.56%
Appasami S. Nickolas	**The European Physical Journal Special Topics (2022)**	**A deep learning-based COVID-19 classification from chest X-ray image: case study**	**93%**
Zohreh Mousavi, Nahal Shahini, Sobhan Sheykhivand, Sina Mojtahedi, Afrooz Arshadie	**Pub Med (2022)**	**COVID-19 detection using chest X-ray images based on a developed deep neural network**	90%
Nigam, B., Nigam, A., Jain, R., Dodia, S., Arora, N., Annappa, B	**Expert Systems with Applications (2021)**	**Covid-19: Automatic detection from x-ray images by utilizing deep learning methods**	93.48%.
Ismael,A.M., Sengur,A.	**Expert Systems with Applications (2021)**	**Deep learning approaches for covid-19 detection based on chest x-ray images**	94.7%

Compared to previous studies, this study produced a result of 99.23%, which is a high value in terms of accuracy in determining the presence of disease. The difference between the previous studies and this study is that the size of the data used was larger in the previous study. To evaluate the performance of the CNN constructed in this study, the precision, recall, and F1-Score for each disease were calculated and shown in <Table 2>. As shown in <Table 2>, in the normal image, precision was 87%, recall was 86%, and F1-Score was 43%. Mild images showed precision of 62%, recall of 51%, and F1-Score of 27.98%, while moderate images showed precision of 59%, recall of 64%, and F1-Score of 30.70%. And in severe images, precision was 57%, recall was 66%, and F1-Score was 30.59%. The evaluation of this experiment shows that it is an excellent result.

Limitations

This study has the following limitations. The problem with automatically classifying diseases is the vastness and integrity of the dataset. If the data is not prepared, it will cause problems with the accuracy of classification. In addition, the doctor's decision-making (diagnosis) at the medical site is not limited to image data, but is based on comprehensive data, and has the limitation that medical decisions cannot be made by machines without the involvement of the doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts but of experts in the field. Therefore, medical staff in the field must participate in the process of developing AI in the medical field.

V. Conclusion

The purpose of this study was to classify COVID-19 CXR images using a CNN modified from AlexNet so that it can be used as an auxiliary method when diagnosing diseases in medical settings. The dataset used for learning was the “COVIDGR-1.0 Dataset”. This dataset was constructed from anonymized X-ray images in close collaboration with a team of radiologists at “Hospital Universitario San Cecilio” in Spain. As a result of the experiment, the AUC was 0.8781 in disease grade classification of CXR images, showing an accuracy of 87.81%, which was ahead of the previous studies reviewed and showed that the experimental results were excellent. To evaluate the performance of the CNN constructed in this study, precision, recall, and F1-Score were calculated for each disease. As a result of the calculation, in the normal image, the precision was 87%, the recall rate was 86%, and the F1-Score was 43%. For mild images, the precision was 62%, the recall was 51%, and F1-Score was 27.98%, and for moderate images, the precision was 59%, the recall was 64%, and F1-Score was 30.70%. In severe images, it showed excellent performance with precision of 57%, recall of 66%, and F1-Score of 30.59%. The research results are expected to be useful in the following fields: First, it can be used as an auxiliary tool for diagnosing lung diseases. To diagnose a disease, the diagnosis is made based on a lot of comprehensive data such as the patient's history, various clinical data, and the patient's living environment. The classification of diseases obtained in this study can be used as an auxiliary tool during the diagnosis process. Second, it was proven through experiments that if the dataset is prepared, it can be used to distinguish diseases other than lung diseases. Third, many medical images are being produced in hospitals. In terms of data management, it is a very important issue to classify and store these videos separately. At this time, if the results obtained in this study are utilized, it will be possible to automatically classify and save images. Fourth, in the medical field, the object to be classified can be imaged using a smartphone and then classified and stored.

Despite these expectations, this study has the following limitations. Preparation of a large dataset for automatic classification of diseases and data integrity. If the data is not prepared or the prepared data is contaminated, it causes problems in the results. In addition, the doctor's decision-making (diagnosis) at the medical site is not limited to image data, but is based on comprehensive data, and has the limitation that medical decisions cannot be made by machines without the involvement of the doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts but of experts in the field. Therefore, medical staff in the field must participate in the process of developing AI in the medical field.

Future research tasks include developing application programs by developing the input stage of the program improving performance, and continuing research in connection with the medical big data server.

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A 58-year-old man with progressive dyspnea suffering from Munier-Kuhn syndrome.

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Abstract

A 58-year-old man who was a former smoker and had a 20-pack-year smoking history presented to the hospital with worsening shortness of breath. Pulmonary function tests revealed mixed obstructive-restrictive physiology. Forced vital capacity (FVC) was predicted at 68%, forced expiratory volume in 1 second (FEV1) at 60% was predicted, FEV1/FVC at 67% was predicted, and Carbon monoxide (DLCO) diffusion capacity is expected to be 70%.

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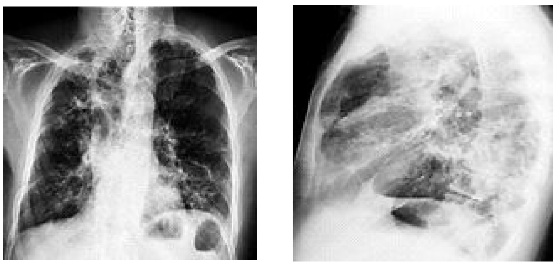
Chest images show increased interstitial density around the hilum. There is massive tracheobronchiomegaly with a tortuous appearance in the airways. There is also a small degree of parenchymal scarring and fibrosis-like reticular perihilar interstitial opacity. CT images show traction bronchiectasis is a finding in the setting of fibrotic lung disease. When lung tissue becomes inelastic due to the formation of dense fibrosis, the airways appear blocked and dilated. Although this patient has dilated airways, the bronchiectasis is greater than the small amount of parenchymal fibrosis seen. Therefore, this process is not caused by parenchymal fibrosis, but rather by inherent pathology of the airway wall. The most frequently reported symptoms of Mounier-Kuhn syndrome are severe cough, difficulty breathing, and recurrent respiratory infections. Patients may complain of chest pain and hemoptysis, but systemic symptoms are rare and require immediate investigation for other diseases. Pulmonary function tests often reveal obstructive pulmonary disease, but in advanced stages there may be limited parenchymal changes, resulting in a mixed appearance, as in a patient's case. Because airway changes are considered irreversible, treatment is aimed at managing symptoms and reducing long-term complications. Recommended lifestyle modifications include quitting smoking and avoiding irritants/particulates. Concurrent COPD or asthma is addressed to limit further morbidity. The infection is treated aggressively, usually requiring broad-spectrum antibiotics to treat atypical infections. The use of expectorants and chest physiotherapy is considered helpful in preventing recurrent infections. Tracheal stenting may be considered if there are specific airways prone to collapse, but the spread of airway involvement limits its potential utility.

Key word: Dyspnea, Chest X-Ray, Chest CT, Munier-Kuhn syndrome

1. History and Radiogram

A 63-year-old man who was a former smoker and had a 20-pack-year smoking history presented to the hospital with worsening shortness of breath. Pulmonary function tests revealed mixed obstructive-restrictive physiology. Forced vital capacity (FVC) was predicted at 68%, forced expiratory volume in 1 second (FEV1) at 60% was predicted, FEV1/FVC at 67% was predicted, and Carbon monoxide (DLCO) diffusion capacity is expected to be 70%.

A chest radiograph was taken, showing postero-anterior and left lateral projections.



(A) P-A **(B) Left lateral**

Figure 1. Chest X-Ray Images

Figure 1 Chest images show increased interstitial density around the hilum. There is massive tracheobronchiomegaly with a tortuous appearance in the airways. There is also a small degree of parenchymal scarring and fibrosis-like reticular perihilar interstitial opacity. A noncontrast chest CT was performed to better evaluate the abnormalities seen on the chest radiograph.

Axial, sagittal, and coronal images are shown.

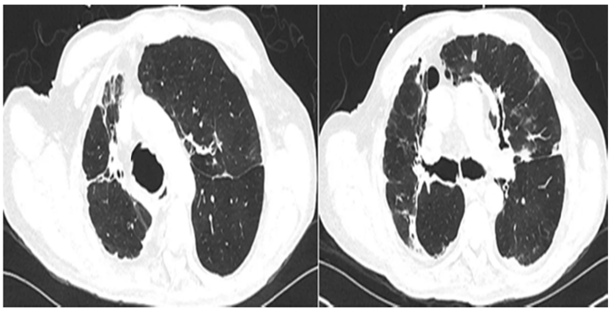


Figure 2. Axial scan images of chest CT

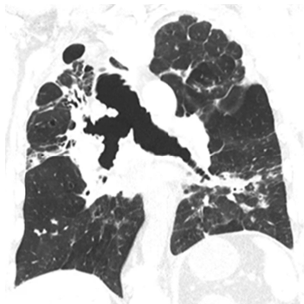


Figure 3. Coronal scan image of chest CT

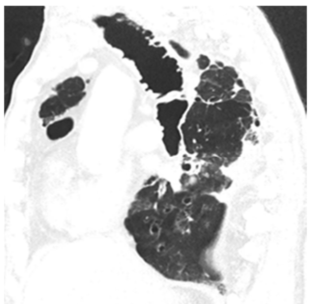


Figure 4. Sagittal scan image of chest CT

Traction bronchiectasis is a finding in the setting of fibrotic lung disease. When lung tissue becomes inelastic due to the formation of dense fibrosis, the airways appear blocked and dilated. Although this patient has dilated airways, the bronchiectasis is greater than the small amount of parenchymal fibrosis seen. Therefore, this process is not caused by parenchymal fibrosis, but rather by inherent pathology of the airway wall.

2. Finding

Radiograph:

tracheobronchial hypertrophy

Thickening of bronchial walls

Interstitial opacities and atelectasis

CT:

Organomegaly (33 mm in diameter)

Main bronchi dilatation (diameter 25 mm)

Bronchiectasis/bronchiolectasis

Tracheal/bronchial diverticula

Parenchymal scarring and volume loss

3. Differential Diagnosis

Cystic fibrosis

Mounier-Kuhn syndrome

Cutis laxa, Marfan syndrome, Ehlers-Danlos syndrome

COPD, bronchitis

Pneumoconioses

4. Diagnosis: Mounier-Kuhn syndrome

Munier-Kuhn syndrome, also known as tracheobronchiomegaly, is a rare medical condition characterized by enlargement of the trachea and main bronchi. This causes the airway walls to weaken and stretch. The disease was first described by Pierre Mounier-Kuhn in 1932. The main features of Munier-Kuhn syndrome include[(1)]:

Bronchiectasis: The trachea (trachea) and bronchi (airways leading to the lungs) become abnormally widened or enlarged.

Weakened airway walls: The walls of the trachea and bronchi become structurally weakened, resulting in reduced elasticity and muscle tone.

Respiratory Symptoms: People with Munier-Kuhn syndrome may experience a variety of respiratory symptoms, including chronic cough, excessive mucus production, recurrent respiratory infections, and difficulty breathing.

Increased risk of complications: Weakened airway walls increase the risk of complications such as recurrent pneumonia and bronchiectasis.

The exact cause of Munier-Kuhn syndrome is not well known. In some cases, there may be genetic factors, and in other cases, it may be caused by acquired factors. Smoking is considered a potential contributing factor. Diagnosis usually involves imaging tests such as a chest x-ray, computed tomography(CT) scan, or bronchoscopy. Pulmonary function tests may also be done to evaluate lung function. Management and treatment of Munier-Kuhn syndrome focuses on resolving symptoms and preventing complications. Treatment may include medications to manage respiratory symptoms, airway clearance techniques, and in severe cases, surgery. Lung infections must be treated immediately to prevent further damage. Because Munier-Kuhn syndrome is a rare disease, comprehensive treatment often requires a multidisciplinary approach involving pulmonologists and respiratory therapists. Regular monitoring and individualized treatment plans are essential to manage the condition and improve the quality of life for affected individuals.

5. Discussion

Mounier-Kuhn syndrome

(1) Pathophysiology

Munier-Kuhn syndrome (MKS) is a disease primarily characterized by tracheal and bronchial wall enlargement. The exact cause is unknown, but it is likely to be due to genetic and/or epigenetic factors, hence the name congenital tracheobronchiomegaly. Pathological examination reveals that the characteristic airway dilatation may be preceded by atrophy of smooth muscle and elastic fibers within the larger airway walls. During inspiration, the airways remain open, but relaxed tracheal and bronchial walls may collapse during expiration. This can lead to obstructive pulmonary physiology, and patients often suffer from COPD in its early stages and are treated for it. Airway relaxation reduces particle removal effectiveness and increases the risk of pulmonary infection, especially for atypical bacteria in the lower respiratory tract. Recurrent infections can lead to bronchiectatic changes in small airways with parenchymal fibrosis, as seen in a patient.

(2) Epidemiology

Approximately 300 cases have been described in the literature, with a ratio of affected males to females of 8:1. The average age of disease onset is the mid-50s, and the proportion of people with Mounier-Kuhn syndrome (MKS) peaks in their early 60s, as do patients. There are equal differences between smokers and non-smokers and may have some association with a predisposition to connective tissue disorders(2).

(3) Clinical presentation

The most frequently reported symptoms are severe cough, difficulty breathing, and recurrent respiratory infections. Patients may complain of chest pain and hemoptysis, but systemic symptoms are rare and require immediate investigation for other diseases. Pulmonary function tests often reveal obstructive pulmonary disease, but in advanced stages there may be limited parenchymal changes, resulting in a mixed appearance, as in a patient's case.

(4) Imaging Features

Imaging is often sought in patients with progressive respiratory distress or recurrent infections, and patients typically have a chest x-ray when symptoms appear. Patients may have symptoms that precede chest x-ray findings, but common findings are tracheal enlargement and bilateral main bronchiectasis. Bronchiectasis may be present with reticular interstitial opacities and volume reduction, indicating post-inflammatory fibrotic changes. High-resolution CT can be diagnostic in the right clinical setting. It can be diagnosed when the tracheal diameter is more than 3 cm and the main bronchial tube diameter is 2 cm to 2.5 cm. Expiratory imaging may show collapse of the larger airways (i.e., crescentic trachea) and air trapping. Bronchiectasis is a hallmark and may present as clustered cystic structures in the subpleural space and may be confused with cystic lung disease or honeycombing. Patients with extensive bronchiectasis may be at increased risk for bronchopleural fistulas and recurrent pneumothorax, which should be considered in patients with a history of MKS and new chest pain. As in this patient, predominant fibrotic changes may be present around the hilum, and there may be varying degrees of volume loss, most likely a sequela of recurrent infection(3).

(5) Differential Diagnosis

Although not as severe as MKS, several other congenital diseases can cause tracheobronchiomegaly. Cystic fibrosis can cause similar pulmonary pathology, but patients are younger, and the airways are typically affected, inflamed, and have extrapulmonary symptoms. Other congenital connective tissue disorders that cause similar airway changes include flaccid dermatosis, Ehlers-Danlos syndrome, Marfan syndrome, and ataxia telangiectasia. COPD causes similar symptoms and can cause acquired tracheomalacia. End-stage fibrotic lung disease can cause irreversible traction bronchiectasis and potentially tracheal dilatation. Moreover, prolonged mechanical ventilation can cause similar relaxation and airway dilatation(4).

(6) Treatment

Because airway changes are considered irreversible, treatment is aimed at managing symptoms and reducing long-term complications. Recommended lifestyle modifications include quitting smoking and avoiding irritants/particulates. Concurrent COPD or asthma is addressed to limit further morbidity. The infection is treated aggressively, usually requiring broad-spectrum antibiotics to treat atypical infections. The use of expectorants and chest physiotherapy is considered helpful in preventing recurrent infections. Tracheal stenting may be considered if there are specific airways prone to collapse, but the spread of airway involvement limits its potential utility.

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Brain tumor classification by CNN

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Abstract

In this paper, we proposed a disease classification method for brain images using CNN. The research dataset collects images of normal, blastoma, meningioma, adenoma, and glioblastoma by brain tumor disease from journals such as NEJM and AuntMinnie and files them in Exam_Brain.Zip. As a result of CNN processing the images for each file folder in the Exam_Brain.zip file 10 times, the AUC was found to be 0.8825. As a result of the experiment, the brain disease classification accuracy of brain magnetic resonance imaging was found to be 88.25%. These results indicate that the results of this study can be used to classify other diseases once the data set is established, and can also be used to classify objects in other industries.

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This study has the following limitations. A challenge in automatically classifying diseases is the vastness and integrity of the data sets. If the data is not prepared, the accuracy of classification will be problematic. Additionally, in the medical field, a doctor's decision-making (diagnosis) is not limited to image data but is made based on comprehensive data, and there is a limitation in that medical decisions cannot be made by machines without the intervention of a doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts, but the domain of experts in the field. Therefore, field medical staff must participate in the process of developing AI in medical settings. Future research tasks include developing applications that improve performance by developing the input stage of the program, and continuing research in connection with medical big data servers.

Key word: Brain MRI, Tumor Classification, CNN, AlexNet, Confusion Matrix, AUC

I. Introduction

Brain tumors have various types and characteristics. Tumor characteristics are classified in various ways based on cell origin, cell shape, tumor location, size, and malignancy level. Glioma is a tumor derived from glial cells, the connective tissue of the brain, and is one of the most common brain tumors. Among gliomas, Astrocytoma is a tumor derived from glial cells and appears in various forms depending on the grade, while Oligodendroglioma is a tumor derived from oligodendrocytes and occurs in the white matter of the brain. Lymphoma is a brain tumor derived from the lymphatic system that mainly occurs in patients with weakened immune function. Neoplastic medulloblastoma is a rapidly growing, isolated brain tumor that commonly occurs in children and originates in the cerebellum. Chordoma is a rare tumor that occurs in the pharyngeal gland and is located at the base of the brain. A brain cell tumor is a brain tumor that originates from the tissue surrounding the cerebrospinal fluid. Ganglioglioma is a benign tumor derived from nerve cells and glial cells and occurs mainly in children and adolescents. Some tumors are benign tumors that originate from the tissue surrounding the cerebrospinal fluid and are relatively less common. Although the types and characteristics of brain tumors are diverse, they are broadly classified into germinomas, meningioma, adenoma, and glioblastoma[1].

Imaging equipment for diagnosing brain tumors includes MRI, SPET, SPECT/CT, PET/CT, and PET/MRI. These devices acquire brain images as digital images, and the acquired images are managed by PACS. Brain tumor is one of the major causes of death among people. The chances of survival can be increased if the tumor is detected and classified correctly at its early stage. Conventional methods involve invasive techniques such as biopsy, lumbar puncture, and spinal tap method, to detect and classify brain tumors into benign (non-cancerous) and malignant (cancerous). A computer-aided diagnosis algorithm has been designed to increase the accuracy of brain tumor detection and classification, and thereby replace conventional invasive and time-consuming techniques.

Neural Network (NN) refers to a computational model that imitates the structure of the human brain to construct an information processing system that resembles a human[2]. NN consists of an input layer, a hidden layer, and an output layer, and a network with multiple hidden layers is called a deep neural network (DNN). Learning with DNN is called deep learning (DL), and DL is achieving high results in many fields such as image classification and object detection. Convolutional Neural Network (CNN) is a DL model that extracts and classifies image features and has recently been actively used in the imaging field[2]. DL models such as CNN have excellent computational capabilities for processing and understanding complex and large amounts of data.

In this paper, we attempt to classify digitally acquired brain images into normal, blastoma, meningioma, adenoma, and glioblastoma by modifying the CNN-based AlexNet using a transfer learning method. Datasets for research were constructed for each brain tumor disease from journals such as NEJM and AuntMinnie. The results of this study believe that it will be possible to automatically classify various types of brain tumors if a dataset is constructed for each disease.

II. Materials and Methods

1. Dataset for research

The dataset for research is collected images of normal, germinoma, meningioma, adenoma, and glioblastoma by brain tumor disease from journals such as NEJM and AuntMinnie, and file them as Exam_Brain.Zip. The data size was a total of 50 images, 10 for each disease.

2. CNN

CNN models are a type of artificial neural network used in DL to evaluate visual information, and these networks can handle a wide range of tasks related to images, sound, text, video, and other media. CNN was created in the late 1990s by Professor Yann Lecunn at Bell Labs[3]. CNN models have input layers, output layers, hidden layers, and millions of parameters, allowing them to learn complex objects and patterns. A convolution and pooling process is used to sample a given input before applying an activation function, where all inputs are partially connected to hidden layers and the fully connected layer at the end is the output layer. The output format itself is the same as the size of the input image. Convolution is a process that combines two functions to generate the output of another function, and the input image is changed by applying a filter to the CNN model. The CNN model was proposed to solve the problems of training time, network size, and number of variables. The CNN model combines the convolution and pooling parts that extract features and the extracted features, it is divided into classification parts[4]. Figure 1 shows the concept of the CNN model.

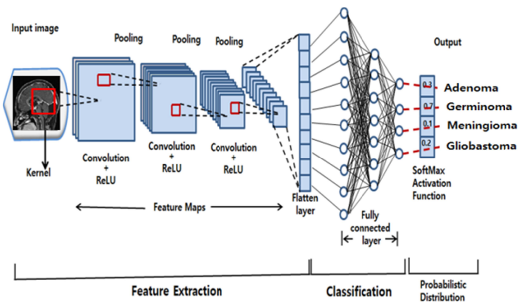


Figure 1. The concept of the CNN model

3. AlexNet

AlexNet is a CNN-structured Neural Network(NN) that won the ILSVRC (imageNet large scale visual recognition challenge) competition held in 2012[5]. The official paper is “ImageNet Classification with Deep Convolutional Neural Network”[5]. It is called AlexNet, named after the first author of the paper, Alex Khrizevsky, and AlexNet brought CNN to the spotlight again. AlexNet was designed as shown in Figure 2 with two GPUs in parallel structure to perform parallel computation[5].

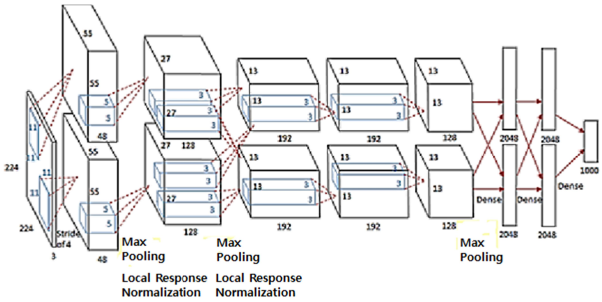


Figure 2. AlexNet with two GPUs in parallel architecture to perform parallel computations.

4. Transfer learning of AlexNet

AlexNet receives “Exam_Brain.Zip” as input and outputs the probabilities of labels and categories in the image. Transfer learning is widely used in DL applications[6]. A pre-trained neural network can be used as a starting point for learning new tasks. Fine-tuning a neural network with transfer learning is usually much faster and easier than training the network from scratch using randomly initialized weights. Learned features can be quickly transferred to a new task using a smaller number of training images, and the transfer learning process of AlexNet is shown in Figure 3[7].

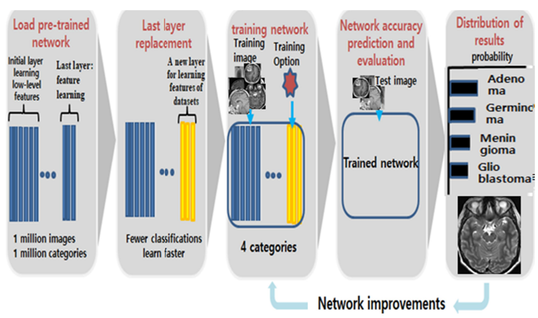


Figure 3. The transfer learning process of AlexNet

III. Experiment and Results

AlexNet CNN was modified and programmed using the transfer learning method to classify the grade of Brain tumor disease in Brain images of "Exam_Brain.Zip" into Adenoma, Germinoma, Meningioma, and Glioblastoma. The experiment used MatLab R2023B on a computer equipped with a GPU. The experimental procedure was performed as shown in Figure 4.

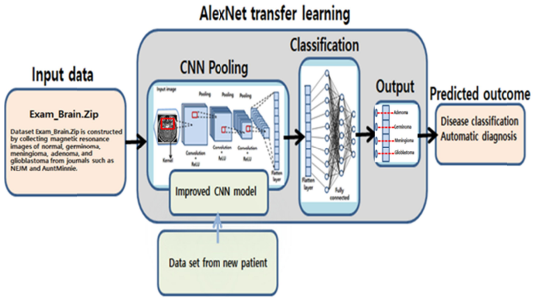


Figure 4. The experimental procedure

Unzipped the Exam_Brain.Zip file and loaded it into the data storage. The images were labeled based on the folder name and the data was saved as an ImageDatastore object. Data stored in the computer was divided into training datasets and validation datasets. The splitEachLabel function is a function that splits the data storage into two new data storages and stores them. The split data was divided into 70% training data and 30% validation data. Sample images were displayed using the algorithm below, with 2images in rows and 3 images in columns, a total of 6 images, as shown in Figure 5. The displayed image was converted from an RGB image to a gray image through a Matlab function, and the normalized image was displayed.

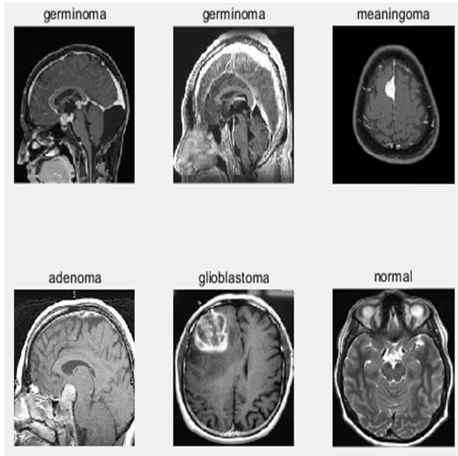


Figure 5. Display of sample images

An experiment was performed to classify brain diseases. The CNN training process for verification is shown in Figure 6. Looking at the CNN training process, the epoch period was short and the training time was also short due to the small amount of data.

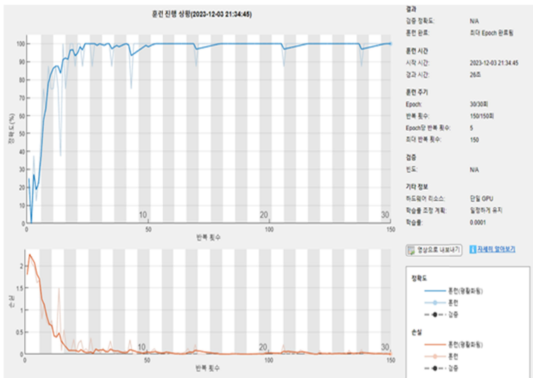


Figure 6. CNN training process

Finally, the verification image was classified using the classify function. The classification images with four disease names are shown in Figure 7 along with the predicted labeling.

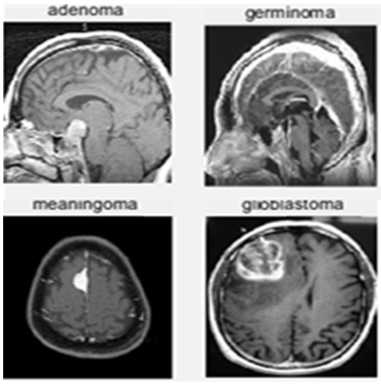
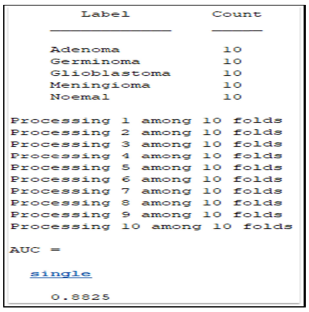


Figure 7. The classification images

CNN processed the images for each file folder in the Exam_Brain.zip file 10 times, and the AUC was found to be 0.8825, as shown in Figure 8.



```
Label            Count
Adenoma           10
Germinoma         10
Glioblastoma      10
Meningioma        10
Noemal            10

Processing 1 among 10 folds
Processing 2 among 10 folds
Processing 3 among 10 folds
Processing 4 among 10 folds
Processing 5 among 10 folds
Processing 6 among 10 folds
Processing 7 among 10 folds
Processing 8 among 10 folds
Processing 9 among 10 folds
Processing 10 among 10 folds
AUC =
  single
    0.8825
```

Figure 8. AUC

To evaluate the effectiveness of the CNN model that learned brain disease classification, a confusion matrix as shown in Figure 9 was obtained. The order of the confusion matrices was arranged alphabetically in the file folders in the Exam_Brain.zip file.

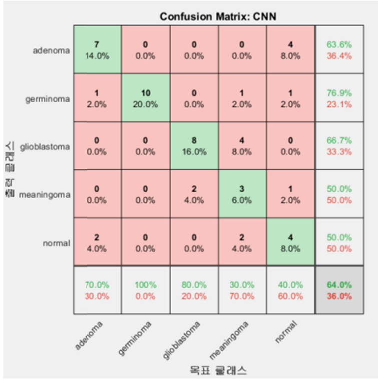


Figure 9. Confusion matrix

The ROC of CNN for brain disease classification is shown in Figure 10. Because the training data was small (50 pieces in total), the shape of the graph appeared in the form of stairs. The area under the x-axis curve (AUC) shown in the graph represents 88.25% of the total area of the graph.

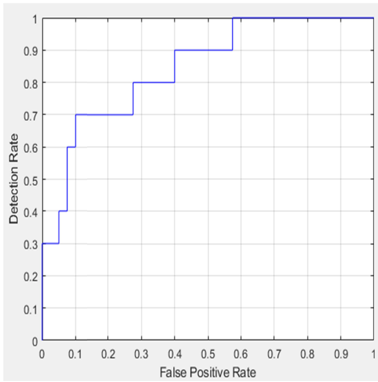


Figure 10. ROC

III. Discussion

In this paper, we proposed a disease classification method for brain images using CNN. Table 1 shows previous studies conducted before this study. The research contents of previous studies are as follows. Pauline John (2012) introduces an efficient method of brain tumor classification, where, the real

Magnetic Resonance (MR) images are classified into normal, non-cancerous (benign) brain tumors and cancerous (malignant) brain tumors. The proposed method follows three steps,(1) wavelet decomposition,(2) textural feature extraction, and (3) classification. The proposed method has been applied to real MR images, and the accuracy of classification using a probabilistic neural network is found to be nearly 100%[8]. Pauline John was conducted through three steps: wavelet decomposition, feature extraction, and classification. However, in this paper, the method of classifying diseases was improved using CNN without going through a separate feature extraction step[8]. Swapnali et al(2014 Swapnali et al(2014) propose an automatic support system for stage classification using an artificial neural network (learning machine) to detect Brain. They present a segmentation method, the k-means clustering algorithm, for segmenting Magnetic Resonance images to detect the Brain Tumor in its early stages and to analyze anatomical structures. A well-known segmentation problem within MRI is the task of labeling the tissue type which includes White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF), and sometimes pathological tissues like tumors, etc. A Probabilistic Neural Network with a radial basis function will be employed to implement an automated Brain Tumor classification. Decision-making was performed in two stages: feature extraction using GLCM and PCA and classification using the PNN-RBF network. The performance of this classifier was evaluated in terms of training performance and classification accuracies. The simulated results show that the classifier and segmentation algorithm provide better accuracy than the previous method. The research they conducted was on segmentation, which is different from research on distinguishing diseases[9]. Ahmed KHARRAT, Karim GASMI, Mohamed BEN MESSAOUD, et al. (2010) propose a hybrid approach for classifying brain tissue in magnetic resonance imaging (MRI) based on genetic algorithm (GA) and support vector machine (SVM). A set of wavelet-based texture features is derived. We extract optimal texture features from normal and tumor regions using spatial gray level dependence method (SGLDM). These features serve as input to the SVM classifier. Feature selection, a big problem in classification techniques, is solved using GA. These optimal features are used to classify brain tissue into normal, benign, or malignant tumors. The performance of the algorithm is evaluated on a series of brain tumor images. However, their study also went through an image decomposition step using the wavelet method, and it was found that images could only be distinguished into normal, benign, and malignant tumors[10]. N. Varuna Shree, T. N. R. Kumar (2018) focused on denoising techniques, gray level co-occurrence matrix (GLCM) feature extraction and DWT-based brain tumor region growth segmentation to reduce complexity and improve performance. Morphological filtering was then performed to remove noise that may have formed after segmentation. A probabilistic neural network classifier was used to train and test the performance accuracy of tumor localization in brain MRI images. The experimental results demonstrated the effectiveness of the proposed technique in identifying normal and abnormal tissues in brain MR images with almost 100% accuracy. In addition, the content of this study is different from the content of this study in that it is a technology for detecting disease areas within a single MRI image. It goes through a preprocessing step of segmentation using DWT[11]. Murugan Arunachalam and Sabeenian Royappan Savarimuthu (2017) state that detecting and segmenting tumor regions in brain images is an important task due to the similarity between abnormal and normal regions. Automatic computer-assisted detection and segmentation of brain tumors has been proposed. The proposed system consists of enhancement, transformation, feature extraction, and classification. The shift-invariant shearlet transform (SIST) is used to enhance brain images. In addition, NSCT (Nonsubsampled Contourlet Transform) is used as a multi-resolution transformation that converts a spatial domain enhanced image into a multi-resolution image. Texture features from Gray Level Co-occurrence Matrix (GLCM), Gabor, and Discrete Wavelet Transform (DWT) are extracted using approximate subbands of NSCT transformed images. These extracted features are trained using a feedforward backpropagation neural network and classified into normal or glioblastoma brain images. Additionally, K-means clustering algorithm is used to segment tumor regions in classified glioblastoma brain images. The proposed method achieved sensitivity of 89.7%, specificity of 99.9%, and accuracy of 99.8%. Their research also showed that the disease area was segmented using DWT within one image and that normal images were distinguished from diseased images (glioblastoma in the brain)[12].

<Table 1> Previous studies conducted before this study

Author	Journal (Year of publication)	Title
Pauline John	International Journal of Scientific & Engineering Research(2012)	Brain tumor classification using wavelet and texture based neural network
Swapnali Sawakare Dimple Chaudhari	International Journal for Research in Emerging Science and Technology (2014)	Classification of Brain Tumor Using Discrete Wavelet Transform, Principal Component Analysis and Probabilistic Neural Network
Ahmed KHARRAT, Karim GASMI, Mohamed BEN MESSAOUD, et al	Leonardo Journal of Sciences (2010)	A Hybrid Approach for Automatic Classification of Brain MRI Using Genetic Algorithm and Support Vector Machine
N. Varuna Shree, T. N. R. Kumar	Brain Informatics (2018)	Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network
Murugan Arunachalam, Sabeenian Royappan Savarimuthu	International Journal of Imaging Systems and Technology(2017)	An efficient and automatic glioblastoma brain tumor detection using shift-invariant shearlet transform and neural networks

In this study, we proposed classifying diseases in brain images using CNN. As a result of the experiment, the classification of brain diseases in brain magnetic resonance images was found to be 88.25% accurate. These results indicate that the results of this study can be used to classify other diseases if a dataset is established and that they can be used to classify objects in other industrial fields. This study has the following limitations. The problem with automatically classifying diseases is the vastness and integrity of the dataset. If the data is not prepared, it will cause problems with the accuracy of classification. In addition, the doctor's decision-making (diagnosis) at the medical site is not limited to image data, but is based on comprehensive data, and has the limitation that medical decisions cannot be made by machines without the involvement of the doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts but of experts in the field. Therefore, medical staff in the field must participate in the process of developing AI in the medical field.

V. Conclusion

In this study, we proposed a method to classify diseases in brain images using CNN. We use transfer learning methods to modify CNN-based AlexNet to classify digitally acquired brain images into normal, blastoma, meningioma, adenoma, and glioblastoma. The research data set collects images of normal, blastoma, meningioma, adenoma, and glioblastoma by brain tumor disease from journals such as NEJM and AuntMinnie and files them with Exam_Brain.Zip. The data size was a total of 50 images, 10 for each disease.

As a result of CNN processing the images for each file folder in the Exam_Brain.zip file 10 times, the AUC was confirmed to be 0.8825. As a result of the experiment, the brain disease classification accuracy of brain magnetic resonance imaging was found to be 88.25%. These results indicate that the results of this study can be used to classify other diseases once a dataset is established, and can also be used to classify objects in other industrial fields.

This study has the following limitations. The challenge with automatically classifying diseases is the vastness and integrity of the data sets. If the data is not prepared, the accuracy of classification will be problematic. Additionally, in the medical field, a doctor's decision-making (diagnosis) is not limited to image data but is made based on comprehensive data, and there is a limitation in that medical decisions cannot be made by machines without the intervention of a doctor. Determining the decision threshold in AI decision-making problems is also an important limitation. This is because setting reference points for sensitivity and specificity is not the domain of AI experts, but the domain of experts in the field. Therefore, field medical staff must participate in the process of developing AI in medical settings.

Future research tasks include developing an application that improves performance by developing the input stage of the program, and continuing research in connection with medical big data servers.

Acknowledgements

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Review: Consideration of nanomedicine, Its Past and Future, and Its Application Possibilities

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Abstract

Nanomedicine is a field that integrates nanotechnology with medicine to revolutionize healthcare. This emerging field promises to improve medical care by facilitating biomedical research, enabling targeted drug delivery, and advancing regenerative medicine. Nanomedicine refers to the use of nanotechnology in medical applications, combining disciplines such as medicine, physics, biology, chemistry, engineering, and optics to diagnose and treat diseases in a more efficient and precise manner. Nanomedicine utilizes nanomaterials, such as nanoshells, nanobiosensors, nanovaccines, nanorobots, and nanocapsules, for various biomedical applications.In conclusion, nanomedicine has the potential to greatly impact healthcare by revolutionizing diagnosis, treatment, and overall medical care [9]. Furthermore, it has the potential to address current limitations in conventional therapies by offering selectivity in targeting tissues, controlled drug release, and protection against premature invivo degradation.

Key word: Nanomaterial, Nanobiosensor, Nanorobot, Nanocapsule, Nanomedicine

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1. Introduction to Nanomedicine

Nanomedicine is a field that integrates nanotechnology with medicine to revolutionize healthcare[1]. This emerging field promises to improve medical care by facilitating biomedical research, enabling targeted drug delivery, and advancing regenerative medicine. Nanomedicine refers to the use of nanotechnology in medical applications, combining disciplines such as medicine, physics, biology, chemistry, engineering, and optics to diagnose and treat diseases in a more efficient and precise manner. Nanomedicine utilizes nanomaterials, such as nanoshells, nanobiosensors, nanovaccines, nanorobots, and nanocapsules, for various biomedical applications [2].

These nanomaterials offer potential advantages over conventional therapies, as they can enhance the effectiveness of drug delivery, provide targeted treatment to specific cells or tissues, improve disease diagnosis through advanced imaging techniques, and even enable the regeneration of damaged tissues[3]. Nanomedicine has seen a surge in research activity over the past decade and is expected to have a significant impact on the prevention, diagnosis, and treatment of diseases. Nanotechnology has the potential to revolutionize healthcare by integrating with medicine to form the field of nanomedicine. This field holds great promise for the future of healthcare, as it combines the power of nanotechnology with the knowledge and understanding of cellular and molecular functions.

Nanomedicine, with its integration of nanotechnology and medicine, has the potential to revolutionize healthcare by enhancing drug delivery, enabling targeted treatment to specific cells or tissues, improving disease diagnosis through advanced imaging techniques, and facilitating the regeneration of damaged tissues[1]. By harnessing the unique properties of nanomaterials, nanomedicine offers a range of advantages over conventional therapies[4]. These advantages include increased drug efficacy, reduced side effects, enhanced tissue penetration, and improved molecular imaging capabilities. In addition, nanomedicine has the potential to overcome many challenges in healthcare, such as drug resistance and limited drug delivery to specific areas of the body, ultimately leading to more effective and personalized treatments for patients.

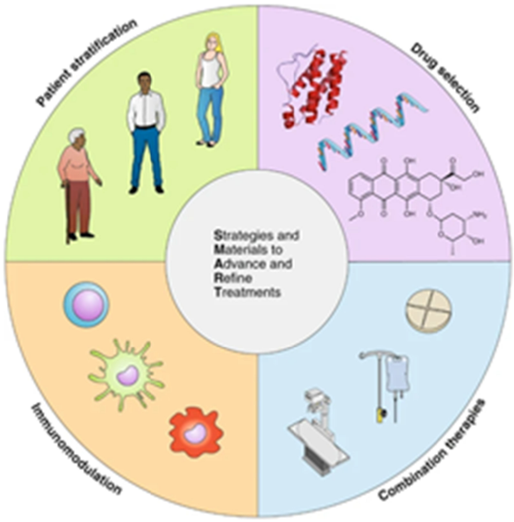

Figure 1. Smart strategies and materials to advance and refine cancer nanomedicine treatment [11].

The field of nanomedicine holds great promise for the future of healthcare, as it combines the power of nanotechnology with the knowledge and understanding of cellular.

2. Understanding the Concept of Nanomedicine

Understanding the concept of nanomedicine is crucial in harnessing the potential of nanotechnology for healthcare purposes. Nanomedicine involves the use of Nanotechnology in various aspects of medicine, such as drug delivery, imaging, diagnostics, and therapy [3].

Nanomedicine offers numerous advantages over traditional approaches to healthcare and medicine.

These advantages include improved drug efficacy, targeted treatment to specific cells or tissues, enhanced disease diagnosis through advanced imaging techniques, and the potential for tissue regeneration. Nanomedicine is a rapidly growing field that aims to revolutionize healthcare and medicine through the use of nanotechnology. By utilizing materials and techniques at the nanoscale, nanomedicine aims to revolutionize healthcare by providing more effective and personalized treatments[5]. Nanomedicine revolutionizes healthcare by integrating nanotechnology with medicine, offering targeted treatment, improved drug delivery, advanced imaging techniques, and potential tissue regeneration, ultimately leading to better outcomes for patients .

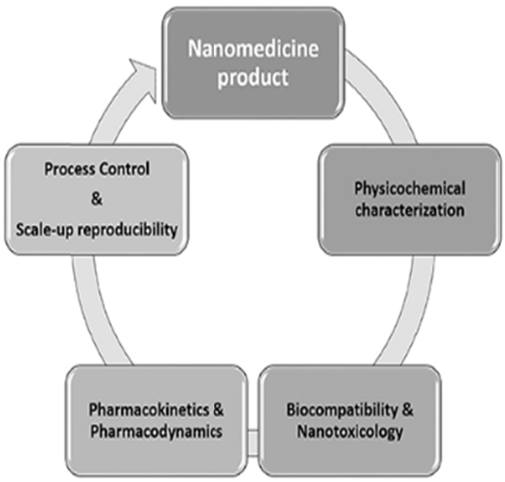

Figure 2. Development of a nanomedicine product and their process

Nanomedicine has the potential to revolutionize healthcare by utilizing nanotechnology to enhance drug delivery, target specific cells or tissues, improve disease diagnosis through advanced imaging techniques, and even facilitate tissue regeneration[1]. Overall, nanomedicine has the potential to bring significant advancements in diagnosis and treatment of diseases by utilizing nanotechnology to improve drug efficacy, reduce side effects, improve molecular imaging capabilities, and overcome challenges in healthcare such as drug resistance and limited drug delivery to specific areas of the body .

In conclusion, nanomedicine is an emerging field that combines the power of nanotechnology with healthcare to revolutionize medicine . With the use of nanotechnology, nanomedicine holds the potential to greatly improve medical care by enhancing drug delivery, enabling targeted treatment, and advancing diagnostic

3. The Evolution of Nanomedicine

Nanomedicine has rapidly evolved as a field that harnesses the power of nanotechnology to revolutionize medicine and healthcare. Utilizing nanotechnology in various aspects of medicine, such as drug delivery, imaging, diagnostics, and therapy, nanomedicine offers numerous advantages over traditionalapproaches to healthcare and medicine. These advantages include improved drug efficacy, targeted treatment to specific cells or tissues, enhanced disease diagnosis through advanced imaging techniques, and the potential for tissue regeneration. Additionally, nanomedicine has the potential to overcome current limitations of conventional therapies by providing selectivity to target tissues, controlled drug release, and protection against degradation or elimination in the body[3]. In summary, nanomedicine is an emerging field that utilizes nanotechnology to advance medicine and healthcare by improving drug delivery, enabling targeted treatment, enhancing diagnostics and imaging, and potentially facilitating tissue regeneration[1]. Overall, nanomedicine is a promising field that has the potential to greatly impact healthcare by improving the prevention, diagnosis, and treatment of diseases. In summary, nanomedicine is an emerging field that combines the power of nanotechnology with healthcare to revolutionize medicine. Overall, nanomedicine has the potential to bring significant advancements in diagnosis and treatment of diseases by utilizing nanotechnology to improve drug efficacy, reduce side effects, improve molecular imaging capabilities, and overcome challenges in healthcare such as drug resistance and limited drug delivery to specific areas of the body. In conclusion, nanomedicine is an emerging field that combines the power of nanotechnology with healthcare to revolutionize medicine.

In conclusion, nanomedicine is an emerging field that holds great potential to revolutionize medicine and healthcare by utilizing nanotechnology to enhance drug delivery, enable targeted treatment, improve diagnostics and imaging, and potentially facilitate tissue regeneration.

4. Applications and Uses of Nanomedicine

Nanomedicine has a wide range of applications and uses in healthcare. These include: nanodiagnostics, targeted drug delivery, regenerative medicine, imaging techniques, diagnostic tools, drug delivery systems, tissue-engineered constructs, implants and pharmaceuticaltherapeutics, and treatments for various diseases including cardiovascular diseases, cancer, musculoskeletal conditions, psychiatric and neurodegenerative diseases, bacterial and viral infections, and diabetes. Nanomedicine has the potential to revolutionize healthcare and medicine through its diverse applications, including nanodiagnostics, targeted drug delivery, regenerative medicine, and advanced imaging techniques. Nanomedicine has the potential to revolutionize healthcare and medicine through its diverse applications, including nanodiagnostics, targeted drug delivery, regenerative medicine, and advanced imaging techniques. Additionally, nanomedicine has the potential to overcome current limitations of conventional therapies by providing selectivity to target tissues, controlled drug release, and protection against premature inactivation[6]. Overall, nanomedicine is an emerging field that holds great potential to revolutionize medicine and healthcare by utilizing nanotechnology to enhance drug delivery, enable targeted treatment, improve diagnostics and imaging, and potentially facilitate tissue regeneration . The field of nanomedicine has seen significant research activity over the past decade, with a focus on applications such as drug delivery, in vivo imaging.

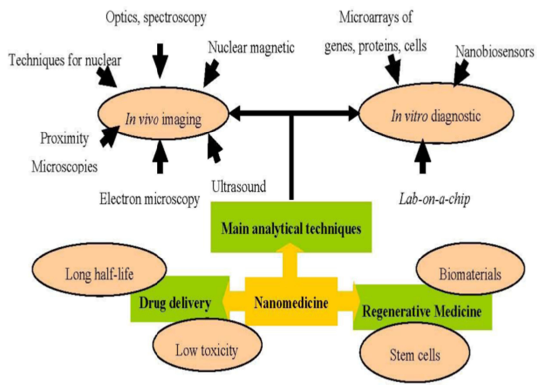

Figure 3. Application area and development prospects

5. Challenges and Opportunities in Nanomedicine

Despite the promising potential of nanomedicine, there are still challenges and opportunities that need to be addressed. These include the safety and toxicity of nanomaterials, regulatory considerations, scalability and cost-effectiveness of nanomedicine technologies, as well as ethicalconsiderations surrounding the use of nanotechnology in medicine.

Furthermore, the integration of nanomedicine into healthcare systems will require collaboration between scientists, clinicians, regulatory bodies, and industry stakeholders. In conclusion, nanomedicine has the potential to revolutionize healthcare and medicine through its diverse applications, including nanodiagnostics, targeted drug delivery, regenerative medicine, and advanced imaging techniques. Additionally, the field of nanomedicine presents both challenges and opportunities [3].

It is crucial to address the safety and toxicity of nanomaterials, regulatory considerations, scalability and cost-effectiveness of nanomedicine technologies, as well as ethical considerations.

6. Recent Advances in Nanomedicine

Recent advances in nanomedicine have shown promise in addressing these challenges and maximizing the potential of nanotechnology in medicine. These advances include the development of biocompatible and biodegradable nanoparticles for drug delivery, the use of nanomaterials with controlled release properties to enhance the efficacy and safety of therapies, and the integration of nanoscale imaging techniques for early disease detection and precise treatment monitoring.

Furthermore, recent innovations in nanomedicine have also led to the development of targeted therapies, where nanoparticles are designed to selectively bind to specific cells or tissues for enhanced treatment efficacy. These targeted therapies have shown promising results in improving the effectiveness of cancer treatments and reducing side effects.

Additionally, advancements in nanomedicine have allowed for the development of multifunctional nanoparticles that can simultaneously deliver drugs, perform imaging, and monitor therapeutic response in real time.

7. Nanomedicine and Healthcare

Nanomedicine has the potential to revolutionize healthcare by providing personalized and targeted treatments for various diseases[1].

These advancements in nanomedicine can lead to improved patient outcomes, reduced healthcare costs, and enhanced quality of life.

Table 1. Nanomedicine and their promising healthcare function.

Application of nanomedicine	Nanomaterial Name & Type	Pharmacological function	Diseases
Nanomedicines in the clinic	Liposome (30-100 nm)	Targeted drug Delivery	Cancer
	Nano particle (Iron oxide, 5-50 nm)	Contrast agent for magneting resonance imaging	Hepatic (Liver)
Nanomedicines under development	Dendrimer (5-50 nm)	Contrast agent for magneting resonance imaging	Cardiovascular Phase III clinical trial
	Fullerene (Carbon bucky ball 2-20 nm)	Antioxidant	Neurodegenerative, Cardiovascular
	Nanoshells (Goldcoated silica 60 nm)	Hyperthermia	Cancer Preclinical

By harnessing the power of nanotechnology, researchers are able to create innovative solutions to long-standing healthcare challenges.

These solutions include the development of nanodiagnostics, which can provide rapid and accurate disease detection, leading to earlier intervention and improved treatment outcomes. In summary, nanomedicine offers great potential in improving healthcare through its advancements in nanodiagnostics, targeted drug delivery, regenerative medicine, advanced imagingtechniques, and multifunctional nanoparticles. Furthermore, nanomedicine also brings forth regulatory considerations, scalability, and cost-effectiveness. Nanomedicine not only brings significant advances in diagnosis and treatment of diseases but also poses ethical considerations. The use of nanotechnology in medicine raises important ethical questions regarding safety, equity, and informed consent.

8. The Future of Nanomedicine

The future of nanomedicine holds immense promise as researchers continue to explore and develop new applications and technologies[7]. These advancements include the use of nanorobots for precise and targeted drug delivery, the development of smart implants that can monitor and adjust treatment in real time, and the integration of nanomedicine with other emerging fields such as artificial intelligence and gene therapy [3].

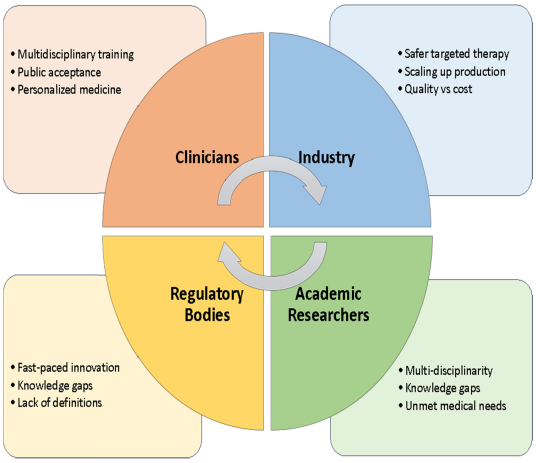

Figure 4. A future aspect on nanotechnology and their application area [11].

With ongoing research and development, nanomedicine has the potential to revolutionize healthcare and improve patient outcomes in the future [8].

In conclusion, nanomedicine has emerged as a powerful tool in healthcare, offering targeted drug delivery, advanced imaging techniques, and personalized treatments[6]. Its potential to simultaneously deliver drugs, perform imaging, and monitor therapeutic response in real time makes it a promising field for the future of healthcare.

9. Ethics and Nanomedicine

With the rapid development and implementation of nanomedicine, ethical considerations become paramount. These considerations include ensuring the safety and efficacy of nanomedicine applications, promoting equitable access to these technologies, protecting patient privacy and autonomy, and ensuring informed consent in the use of nanomedicine. Furthermore, the potential societal impact of nanomedicine must also be considered, including issues related to the distribution of resources, the potential for exacerbating existing health inequalities, and the ethical implications of enhancing human capabilities through nanotechnology. In conclusion, nanomedicine has the potential to revolutionize healthcare by overcoming current limitations in diagnosis, treatment, and management of human disease [8].

10. The Impact of Nanomedicine on Modern Medicine

In summary, nanomedicine has the potential to significantly advance the field of medicine by improving diagnosis, treatment, and healthcare delivery. However, as with any new technology, ethical considerations must be carefully addressed to ensure that these advancements are used responsibly and ethically. The field of nanomedicine has the potential to revolutionize healthcare and improve patient outcomes [9].

However, there are still several challenges that need to be addressed, such as bridging the gap between laboratory research and clinical practice, ensuring regulatory compliance and standardization, addressing biosafety concerns, and considering the cost-effectiveness of nanomedicine[10].

Additionally, it is crucial to consider the long-term societal, economic, and ethical implications of nanomedicine to ensure that its benefits are equitably distributed and that potential risks are adequately mitigated. Nanomedicine has the potential to transform healthcare by revolutionizing diagnosis, treatment, and overall medical care [8].

In conclusion, nanomedicine has the potential to greatly impact healthcare by revolutionizing diagnosis, treatment, and overall medical care[9]. Furthermore, it has the potential to address current limitations in conventional therapies by offering selectivity in targeting tissues, controlled drug release, and protection against premature invivo degradation.

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Review: Insight of Medical Imaging for Precision Medicine In Focusing on Radiomics Aspect

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Abstract

Precision medicine is a revolutionary medical approach that takes into account individual variations in genes, environment, and lifestyle to tailor treatment and prevention strategies for each patient. One crucial aspect of precision medicine is medical imaging, which plays a fundamental role in the accurate assessment and diagnosis of diseases. By utilizing various imaging modalities, such as MRI, CT scan, and PET scan, doctors can obtain detailed information about a patient's condition and make informed decisions about the most effective therapeutic options. Furthermore, imaging techniques like radiomics have emerged as a promising tool in precision medicine. By extracting quantitative data from medical images, radiomics allows for objective and quantitative analysis of the biological characteristics of diseases. This information can then be correlated and integrated with genomic data to further enhance our understanding of diseases, a concept known as radiogenomics. Imaging plays a vital role in the development of precision medicine. Radiomics, based on high-throughput medical imaging, allows for the extraction of vast amounts of data from medical images to perform objective and quantitative analysis of the biological characteristics of diseases. This is crucial for tumor diagnosis, differential diagnosis, prognosis evaluation, and prediction of treatment response. Medical imaging, specifically radiomics, has greatly advanced the field of precision medicine by providing a comprehensive analysis of tumors and extracting quantitative data from medical images. This data can be correlated and integrated with genomic information to enhance our understanding of diseases and enable personalized treatment plans. In summary, medical imaging, particularly radiomics, plays a central and vital role in the development of precision medicine.

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Key word: Radiomics, Radiogenomics , Medical Imaging, Personalized Treatment, Precision Medicine

1. Understanding Precision Medicine

Precision medicine is a revolutionary medical approach that takes into account individual variations in genes, environment, and lifestyle to tailor treatment and prevention strategies for each patient [1].

One crucial aspect of precision medicine is medical imaging, which plays a fundamental role in the accurate assessment and diagnosis of diseases. By utilizing various imaging modalities, such as MRI, CT scan, and PET scan, doctors can obtain detailed information about a patient's condition and make informed decisions about the most effective therapeutic options. Furthermore, imaging techniques like radiomics have emerged as a promising tool in precision medicine[2]. By extracting quantitative data from medical images, radiomics allows for objective and quantitative analysis of the biological characteristics of diseases [3]. This information can then be correlated and integrated with genomic data to further enhance our understanding of diseases, a concept known as radiogenomics[4]. Imaging has the potential to revolutionize precision medicine by providing valuable insights into a patient's unique genetic makeup, environmental factors, and lifestyle choices[3]. This data can then be used to personalize treatment plans and improve patient outcomes.Medical imaging, particularly radiomics, is a crucial component of precision medicine as it allows for the extraction of detailed quantitative data from medical images. This data can then be correlated and integrated with genomic information to enhance our understanding of diseases and tailor treatment plans for individual patients. Imaging plays a central role in the development of precision medicine, specifically through the use of radiomics. Radiomics, through the conversion of medical images into quantifiable features, enables a comprehensive analysis of the total tumor at a three-dimensional level[5]. By capturing information related to tumor pathophysiology, radiomics acts as a virtual whole tumor biopsy, providing clinicians with a wealth of data for personalized treatment plans and decision-making. Imaging, particularly radiomics, has emerged as a powerful tool in precision medicine. It allows for the extraction of detailed quantitative data from medical images, which can be correlated and integrated with genomic information to enhance our understanding of diseases and tailortreatment plans for individual patients. Imaging, particularly radiomics, is at the forefront of precision medicine, enabling the extraction of detailed quantitative data from medical images.

Imaging plays a vital role in the development of precision medicine. Radiomics, based on high-throughput medical imaging, allows for the extraction of vast amounts of data from medical images to perform objective and quantitative analysis of the biological characteristics of diseases [3]. This is crucial for tumor diagnosis, differential diagnosis, prognosis evaluation, and prediction of treatment response. Medical imaging, specifically radiomics, has greatly advanced the field of precision medicine by providing a comprehensive analysis of tumors and extracting quantitative data from medical images. This data can be correlated and integrated with genomic information to enhance our understanding of diseases and enable personalized treatment plans. In summary, medical imaging, particularly radiomics, plays a central and vital role in the development of precision medicine.

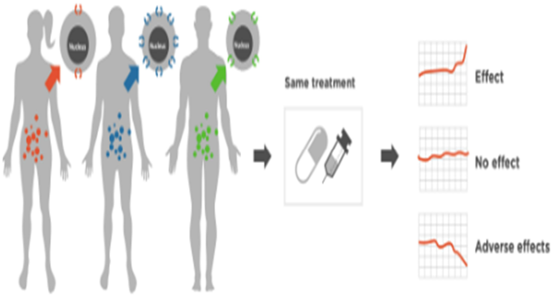

Figure 1. Traditional medicine: Same treatment for all, cancer patient with e.g colon cancer receive the same therapy even though they have different biomarkers

2. Role of Medical Imaging in Precision Medicine

The role of medical imaging in precision medicine is crucial as it allows for the extraction of detailed and quantitative data from medical images. This data, obtained through techniques like radiomics, provides valuable insights into the biological characteristics of diseases. By integrating this imaging data with genomic information, we can enhance our understanding of diseases and develop personalized treatment plans for patients. Additionally, medical imaging can be utilized in clinical-decision support systems to improve medical decision-making by providing objective and quantitative analysis of tumors. By leveraging high-throughput medical imaging techniques such as radiomics, precision medicine can take advantage of the wealth of data available in medical images to enhance diagnosis and treatment planning for individual patients. The integration of radiomics, which extracts quantitative data from medical images, with genomic information has paved the way for precision medicine[4]. Using radiomics to extract quantitative data from medical images has revolutionized the field of precision medicine[5]. Through radiomics, medical imaging has transformed from a diagnostic tool to a key component of precision medicine by providing detailed information about tumor pathophysiology.

In recent years, medical imaging has expanded its role in precision medicine by incorporating radiomics, a technique that extracts highly detailed and quantifiable features from medical images.

This allows for a more comprehensive analysis of diseases and enables objective and quantitative evaluations of tumors in terms of diagnosis, differential diagnosis, prognosis evaluation, and prediction of treatment response. As a result, medical imaging, particularly radiomics, has become an essential tool in precision medicine [2].

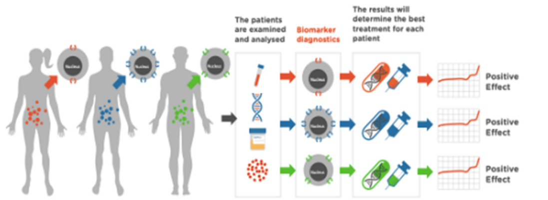

Figure 2. Innovative medicine: Personalized medicine, Cancer patients with e.g. colon cancer receive a personalized therapy based on their biomarkers [15]

3. Advancements in Medical Imaging Techniques

Advancements in radiological image processing techniques have led to the development of radiomics, which allows for the extraction of qualitative and quantitative data from clinical images [4].

This data can then be correlated and integrated with genomic information, resulting in a field known as radiogenomics. Radiogenomics is an emerging precision medicine approach that combines radiomics data with genomic data to provide a deeper understanding of diseases and personalize treatment plans for patients based on their individual characteristics. In the context of personalized precision medicine, medical imaging is rapidly evolving from being a mere diagnostic tool to playing a central role[6]. Medical imaging, specifically radiomics, is an essential component of precision medicine, enabling objective and quantitative analysis of tumors and providing valuable information for diagnosis, prognosis evaluation, and treatment planning[3]. Radiomics, a cutting-edge field in medical imaging, has revolutionized precision medicine. With the increasing volume of data and complexity in decision-making processes, the field of precision medicine has emerged to address the variability of patients and diseases [7].

By analyzing radiomics data, which involves the extraction of quantitative features from medical images, precision medicine can better understand tumor heterogeneity in a noninvasive, economical, and repeatable way. Radiomics provides highly detailed and quantifiable information about tumor pathophysiology, allowing for a comprehensive analysis of diseases and personalized treatment plans based on individual characteristics. Additionally, radiomics does not require invasive sampling inside the tumor like biopsies do, making it a less burdensome and more accessible method for obtaining patient information [8].

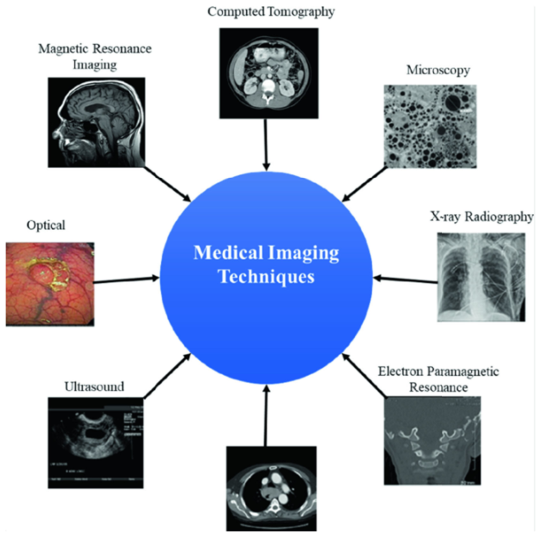

Figure.3 Medical Imaging Techniques in modern medicine [16]

4. Medical Imaging Tools for Diagnosis and Treatment

Radiomics has proven to be a valuable tool in tumor diagnosis, differential diagnosis, prognosis evaluation, and prediction of treatment response[3].

The use of radiomics in medical imaging has provided clinicians with a wealth of information regarding the biological characteristics of diseases.

This information can aid in accurate diagnosis, treatment planning, and monitoring of patients.Radiomics has also opened up new avenues in precision medicine by allowing for the integration of radiomics data with genomic information[4]. This integration, known as radiogenomics, provides a deeper understanding of diseases by identifying imaging correlates of specific tumor genotypes or molecular phenotypes [9]. Furthermore, the computational approach of radiomics allows for the correlation and integration of radiological data with genomics and other precision medicine data[4]. This integration enhances the ability to identify biomarkers, predict treatment response, and develop personalized treatment strategies.Medical imaging, particularly radiomics, has become an essential component of precision medicine[3].

It allows for a more comprehensive and individualized approach to patient care, leading to improved diagnosis, treatment planning, and monitoring of diseases. In summary, medical imaging, specifically radiomics, plays a crucial role in the development and implementation of precision medicine.

5. Impact of Precision Medicine on Healthcare

The emergence of precision medicine has revolutionized healthcare by shifting the focus from a one-size-fits-all approach to a personalized and targeted treatment strategy for each patient. Imaging technologies, such as radiomics, have played a central role in enabling precision medicine. Radiomics, with its ability to extract quantitative features from medical imaging in a high-throughput manner, provides valuable insights into the biological characteristics of diseases. These insights help healthcare providers make more informed decisions regarding diagnosis, treatment selection, and prediction of patient outcomes. By integrating radiomics data with genomic information, radiogenomics has further enhanced the precision medicine approach by identifying imaging correlates of specific tumor genotypes or molecular phenotypes [4].

Incorporating radiomics into precision medicine allows for a more comprehensive understanding of diseases, enabling the development of personalized treatment strategies based on each patient's unique characteristics[7]. This integration of radiomics and genomics data is essential in developing targeted therapies and predicting treatment response, ultimately leading to more successful outcomes for patients [4].

The field of radiomics in precision medicine has the potential to greatly impact healthcare by providing a more comprehensive and individualized approach to patient care. With the ability to extract detailed quantitative features from medical images, radiomics enables a deeper understanding of disease phenotypes and tumor heterogeneity[7]. These insights can guide treatment decisions, including selecting the most effective therapies and monitoring treatment response over time. Furthermore, the integration of radiomics data with other sources, such as electronic health records and patient-reported outcomes, can provide a holistic view of a patient's health status and aid in the development of personalized treatment plans. In summary, imaging, particularly radiomics, has a vital role in the development of precision medicine. By leveraging the vast amount of data extracted through radiomics, healthcare providers can make evidence-based clinical decisions, leading to more effective and targeted treatments for patients. In summary, imaging, particularly radiomics, plays a vital role in the development of precision medicine [3].

6. Challenges in Implementing Precision Medicine

One challenge in implementing precision medicine is the computational intensity of genomic analysis and radiomics[10]. The analysis of genomic data and the extraction of quantitative image features through radiomics generate a large amount of data that require significant computational power and resources. Additionally, integrating and analyzing these different types of data collectively, such as genomics, radiomics, and clinical data, presents further computational challenges. Another challenge is the need for standardization and harmonization of radiomics and genomics data across different imaging modalities and genomic platforms.

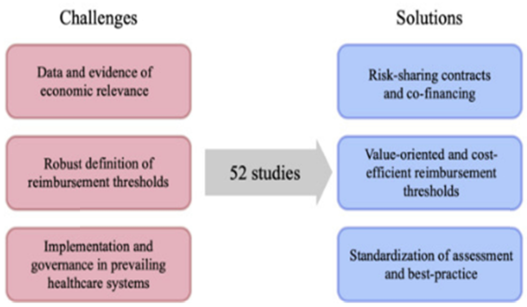

Figure 4. Integration of personalized medicine in healthcare systems[16]

This standardization is essential for ensuring the accuracy and reproducibility of radiomics and genomics analyses, as well as for enabling data sharing and collaboration among different research institutions. Furthermore, the variability and complexity of patients and diseases also pose challenges in implementing precision medicine[7]. Healthcare providers must consider the individual variability of patients and diseases when developing personalized treatment plans. Additionally, there is a need to integrate precision medicine data, which focuses on an individual's health, with public health data through the use of Big Data tools[4]. This integration allows for the aggregation, analysis, and collective interpretation of data on a larger scale, leading to improved population health outcomes.

Overall, while there are challenges in implementing precision medicine, such as computational intensity, standardization, and variability of patients and diseases, the use of imaging and radiomics in precision medicine holds great promise for improving patient outcomes through personalized and targeted treatments[7].

7. The Future of Precision Medicine and Medical Imaging

The future of precision medicine and medical imaging is promising.Advancements in imaging technology and data-driven analysis methods like radiomics are revolutionizing the field of precision medicine[11]. These advancements enable the extraction of quantitative features from medical images, providing valuable information for diagnostic, prognostic, and predictive purposes. Integrating radiomics data with genomic data, known as radiogenomics, allows for a more comprehensive understanding of the underlying molecular characteristics of diseases and how they manifest visually in medical images[4].

This integration opens up possibilities for more targeted and personalized treatment approaches, as well as the identification of new biomarkers and therapeutic targets. Additionally, the integration of radiomics and genomics data across different imaging modalities and genomic platforms is crucial for standardization and ensuring the accuracy and reproducibility of results [12].

By harmonizing data processing and developing specific standards, the integration of genomics and radiomics into the data system can greatly enhance the potential of precision medicine for improving patient care .

With the creation of high-quality, ideally public, datasets that integrate radiomics, genomics, and proteomics information, along with clinical-prognostic and neuropathological data, the implementation of big data analysis in precision medicine can reach its full potential [13].

These datasets will not only facilitate research and the development of new treatments, but also pave the way for more personalized and precise clinical decision-making. Furthermore, the use of big data tools in combination with precision medicine data has the potential to revolutionize public health on a larger scale [4].

In conclusion, the utilization of medical imaging and radiomics in precision medicine is a promising approach that can provide valuable quantitative information about diseases and patients [11].

8. Ethical Considerations in Precision Medicine

Ethical considerations are paramount in the field of precision medicine, especially when it comes to medical imaging and radiomics. There are several ethical considerations that need to be addressed: 1. Privacy and consent: As medical imaging involves the collection and storage of personal health information, it is important to ensure patient privacy and obtain informed consent for the appropriate use and sharing of their data.2. Data sharing and ownership: With the integration of different data sources in precision medicine, including radiomics and genomics, there is a need to establish clear guidelines for data sharing and ownership. This includes determining who has access to the data, how it can be used, and ensuring that individuals involved in data collection and analysis adhere to ethical standards and protect patient privacy. Furthermore, there is also a need to address potential biases and disparities that may arise in the application of precision medicine.

This includes ensuring equitable access to precision medicine technologies and addressing potential biases in the data and algorithms used for diagnosis and treatment. Additionally, there is an ethical responsibility to ensure that the implementation of precision medicine does not lead to undue burden or harm for patients. This may involve monitoring potential risks and adverse effects, as well as addressing issues of affordability and accessibility in order to ensure equitable healthcare for all individuals. In conclusion, while medical imaging and radiomics hold great potential for precision medicine, it is important to approach their implementation ethically and address considerations such as privacy, consent, data sharing and ownership, potential biases, equitable access, and potential risks and harms[6].

9. Success Stories of Precision Medicine Using Medical Imaging

Precision medicine has shown promising successes in various fields of healthcare, thanks to the integration of medical imaging and radiomics. One success story comes from the field of oncology, where precision medicine has revolutionized cancer treatment. By utilizing radiomics to analyze tumor heterogeneity and extract quantitative features from medical images, clinicians can tailor treatments based on the specific characteristics of a patient's tumor [7].

This personalized approach has led to improved diagnostic accuracy, treatment selection, and patient outcomes. For example, in lung cancer, radiomics has been used to predict the response to chemotherapy, allowing for a more targeted and effective treatment plan. Another success story is in the field of neurology, where precision medicine has greatly advanced the diagnosis and treatment of neurological disorders. Using medical imaging and radiomics, clinicians can analyze brain scans to identify unique patterns and biomarkers associated with specific neurological conditions. This allows for early detection, accurate diagnosis, and personalized treatment strategies. In cardiology, precision medicine using medical imaging has also proven to be transformative. Radiomics has allowed for the identification of specific features in cardiac imaging that can predict the risk of cardiovascular events, such as heart attacks or strokes. By applying precision medicine principles to these cases, physicians can develop individualized treatment plans and interventions to manage the patient's cardiovascular health more effectively. Overall, medical imaging and radiomics have demonstrated their value in advancing precision medicine[3].

Not only do they enable more accurate diagnoses and treatment selection, but they also contribute to a personalized approach that takes into account the unique characteristics of each patient and their disease. Furthermore, the implementation of precision medicine using medical imaging comes with several considerations that need to be addressed. These include standardization of imaging protocols and analysis methods, data management and integration, and ethical considerations regarding patient data privacy.

10. The Intersection of Artificial Intelligence and Precision Medicine

The intersection of artificial intelligence and precision medicine has further enhanced the capabilities of medical imaging for personalized healthcare. Using artificial intelligence algorithms, medical images can be analyzed in a more efficient and accurate manner, allowing for the extraction of valuable insights and patterns that may not be immediately apparent to the human eye. This integration of artificial intelligence and precision medicine in medical imaging has the potential to revolutionize healthcare by providing clinicians with more comprehensive and precise diagnostic information. Additionally, the use of neural networks in medical imaging can aid in image interpretation and decision-making. These technologies can identify subtle patterns and features in medical images that may be indicative of specific diseases or conditions, enabling earlier detection and intervention. In conclusion, medical imaging plays a vital role in precision medicine by providing valuable insights into intra-regional heterogeneity of abnormal tissues. This information can then be used to develop targeted treatment plans and interventions for individual patients, leading to improved outcomes in personalized healthcare. In summary, medical imaging is a crucial component of precision medicine by providing quantitative imaging biomarkers and aiding in the diagnosis, prognosis, and personalized treatment planning of patients. It enables clinicians to make more informed decisions based on accurate and detailed information about a patient's condition. Moreover, radiomics and the analysis of medical images using artificial intelligence and machine learning algorithms can contribute to a deeper understanding of tumor characteristics, enabling more precise diagnosis and prediction of treatment response[14].

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