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THE EFFECTIVENESS OF EXTRACTING GOOD FEATURES IN DEEP LEARNING FOR DETECTING TUMORS IN MEDICAL IMAGES

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Abstract

Accurate detection of cancerous tumors is currently considered a critical issue in clinical diagnostics. Artificial intelligence algorithms on computers aid in accurate diagnosis with the help of convolutional neural networks (CNNs), yielding promising results. Extracting appropriate features is an important aspect of medical image diagnosis. AI techniques, including deep learning, help provide accurate results and eliminate the need for radiation exposure from medical devices such as computed tomography (CT) scans and magnetic resonance imaging (MRI). In this study, we propose a methodology based on extracting and learning good features to work with a deep learning model. We train the algorithm on images from a standard database derived from magnetic resonance imaging (MRI) and computed tomography (CT). The proposed method relies on removing features that do not affect the neural network and enhancing features that recur during iterations and training cycles. The results confirm that models using enhanced and enhanced features yield more accurate results compared to models that rely on random feature extraction. In the future, it is possible to enhance the types of features that have an impact on all types of AI algorithms.

Key Words: Feature Extraction, Medical Image, Tumor Detection, Deep Learning.

1.Introduction

Due to technological advancements, medical imaging has played a vital role in healthcare. Imaging, diagnosis, and monitoring are vital for the treatment of many types of tumors [1]. With cancer being so common and early, accurate diagnosis playing a key role in treatment, there is a growing need for technologies like artificial intelligence (AI), especially deep learning, to improve medical systems and imaging diagnostics. Tumor detection remains a

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top priority, which helps improve treatment outcomes by increasing accuracy and reducing the time needed for diagnosis [2].

Convolutional neural networks (CNNs) are among the most vital deep learning algorithms, showing impressive performance in analyzing, classifying, and detecting medical images [3]. Their capacity to automatically learn and recognize complex patterns has helped identify early changes, enabling earlier disease detection. These models depend on extracted features that accurately describe the image. Medical imaging, such as MRI and CT scans, often has blurry or low-quality images due to the safe distance maintained between the patient and the equipment. Going beyond this distance can be hazardous for the human body [4]. Therefore, reliance on digital images and their enhancement is essential, as they are highly secure.

Feature extraction is essential in deep learning, serving not just as a byproduct but also significantly influencing model interpretability and clinical usefulness [5]. All features can be derived from deep learning, such as intensity, size, texture, border-to-overall ratio, and intensity. In machine learning, features are often manually extracted, using methods like local binary patterns (LBP), statistical analysis, or histograms of oriented gradients (HOGs), which also depend on field expertise. However, traditional machine learning has limitations and struggles to interpret complex patterns. Deep learning overcomes this by extracting features across multiple layers, with each layer learning from the previous one to understand complex pixel patterns [6].

The features learned by a deep network are often unequal in importance, and not all of them are effective for deep learning [7]. Conversely, features that are confusing or ineffective negatively impact the results. Much of the increased complexity is due to these ineffective features, which reduce the interpretability of the proposed model. Hence, the importance of feature extraction strategies and their significance in improving deep learning. Many methods have been used in this field, including transfer learning, residual connections, attention mechanisms, and feature selection algorithms, also known as redundant feature elimination (RFE), all to enable the model to focus on regions of greatest importance in the image [8]. Hence, the importance of incorporating clinical knowledge into the extraction of important features, such as focusing on regions of high importance, such as tumors, and accurate diagnosis.

This paper explores the effectiveness of feature extraction in a deep learning model and simulates it on medical images in the context of tumors and their diagnosis. The impact of the extracted features and their strategies on the overall performance, robustness, and distribution of the deep learning model is also studied. The study investigates the accuracy of diagnosis and its relationship to the CNN architecture, which is enhanced by feature extraction technology. This study contributes to the development of artificial intelligence systems and algorithms for the accurate diagnosis of cancerous tumors.

Hence, the clear objectives of this manuscript can be established:

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- To evaluate the feature extraction process and its importance in deep learning for cancer detection.
- To compare feature extraction methods within the deep learning algorithm architecture.

The results of this study will impact the accuracy of cancerous tumor detection and reduce exposure to radiation from imaging devices, which is harmful to human health.

2.Related work

Recently, deep learning has made significant progress in the field of medical image analysis, particularly in tumor detection. This is primarily due to the adaptability of deep learning, particularly with convolutional neural networks (CNNs), and its ability to extract features derived from the properties of medical images [9]. Previously, traditional methods relied on manual hierarchical feature extraction. Deep learning has replaced this manual intervention through multi-level learning. A study by [10] confirmed the role of convolutional neural networks and achieving classification accuracy in identifying skin diseases by combining some of the extracted features. This is where the power of features impacts deep learning models. Another study by [11] identified a comprehensive survey of various algorithms that rely on extracted features and focus on segmenting features to obtain the best structure for deep learning when diagnosing cancerous diseases using various imaging devices such as magnetic resonance imaging, computed tomography, and X-rays [12].

[13] Proposed a model for chest imaging using the CheXNet technique, which is structured as a CNN based on DenseNet. The model is trained to accurately detect pneumonia in chest x-rays. This algorithm achieved strong performance with the same accuracy as practicing specialists. The study focused on reclassifying features at each stage of classification in a hierarchical manner. In the field of brain tumors, [14] used an improved CNN model as the basis for a deep learning algorithm for classifying MRI images. The model worked on merging the closest features and treating them as a single vector to achieve accuracy comparable to that achieved by physicians in this field. [15] Presented a study to build a model based on decoding and median structure, and using attention mechanisms to enhance tumor accuracy by identifying the most useful regions in the image. These attention mechanisms enhance the difference in planning maps by deconvolving the correlations to obtain the best clear image of the tumor. Consequently, features can be extracted for better and more accurate classification.

One of the most recently emerging models is transfer learning, which relies on feature extraction to aid classification in medical fields. A study [16] emphasized the importance of fine-tuning models, whether pre-trained or from scratch, by comparing models during classification. This confirms the relationship between good feature extraction and output accuracy. This study demonstrated that a wide range of training datasets has a significant impact on the results, as in training models on standard datasets such as ImageNet. This reduces the need to work on specific data-intensive models. Some studies have explored hybrid approaches that rely on different features from multiple models, as in [17]. The study

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relied on combining features in deep neural networks to stabilize inputs across the layers of the neural network, which yielded good results in breast cancer detection.

Recently, there has been a focus on clinical applications and the impact of extracted features on the reliability of artificial intelligence algorithms. Class activation mapping (CAM) and gradient-based attention techniques have been widely used to capture the effect of features on the outcome [18]. Despite the development of these models, challenges remain regarding the feasibility of utilizing all features in models, selecting those that are resistant to noise and distortion, and their contribution to solving clinical problems. Hence, the effective role of features and deep learning algorithms in cancer detection emerges, demonstrating the effectiveness of models that rely on automatic feature variability. This study contributes to the systematic analysis of features in deep learning and improves the method to match the classification accuracy for tumor detection in medical images.

3.Feature extraction strategy

Feature extraction is an important aspect of deep learning and machine learning algorithms, especially in medical image analysis. Tumor diagnosis is achieved by identifying patterns, learning the connections between them, and identifying the features that distinguish between them [19]. The process of distinguishing between them depends on whether the tissue is healthy or diseased. Using convolutional neural networks (CNNs), features are automatically extracted sequentially, determined by the layers that comprise the neural network. Important features are then focused on, while those that do not affect the process or outcome are ignored. Visually complex features are captured and abstracted from the medical image through edges and textures in the initial layers, and their complexity increases in the subsequent, deeper layers, representing tumors [20].

The features extracted vary in importance from one to another in deep networks. Some are useless or affected by noise, as in the case of heterogeneous data or small training data. In the medical field, there are many challenges that can be overcome in extracting good features that are robust and have strong, interpretable correlations, making them clinically reliable and amenable to deep learning [21].

We can consider the medical image as I and F as a deep learning model, then extracting the hierarchical feature will be :

$$f^{(l)} = F^{(l)}(I),\ s.t. l = 1\ to\ L \qquad (1)$$

Where the $f^{(l)}$ represents the feature at layer l, and $F^{(l)}$ denotes a transformation or convolution of the l layer, while L represents the total layers in the network [22].

Can illustrate the early layer as $l \approx 1$like low-level features from textures or edges,

$$f^{(1)} \approx detection\ of\ \left(texture\ or\ edge(I)\right) \qquad (2)$$

Then the deep layers will encode as $l \approx L$ to represent the tumor at a high level:

$$f^{(L)} \approx Tumor\ embedding\ of\ I \qquad (3)$$

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The quality of features, starting from the first step of learning features, such that f=[$f1$,$f2$,…,fD], can illustrate the extracted feature in a certain vector D, where the feature f_i is related to the detection target y through tumor classification [23].

4.Proposed Method

The primary objective of the proposed method is to evaluate and enhance the feature extraction mechanism of an AI model, namely deep learning, in the medical field, specifically tumor detection. In the proposed method, we integrate convolutional neural networks (CNNs), which are pre-trained on a standard database, and explore how to optimize features to be computationally efficient and diagnostic. The proposed method consists of five sequential stages, starting with preprocessing and ending with evaluation of the output to be superior to existing methods. As illustrated in Figure 1.

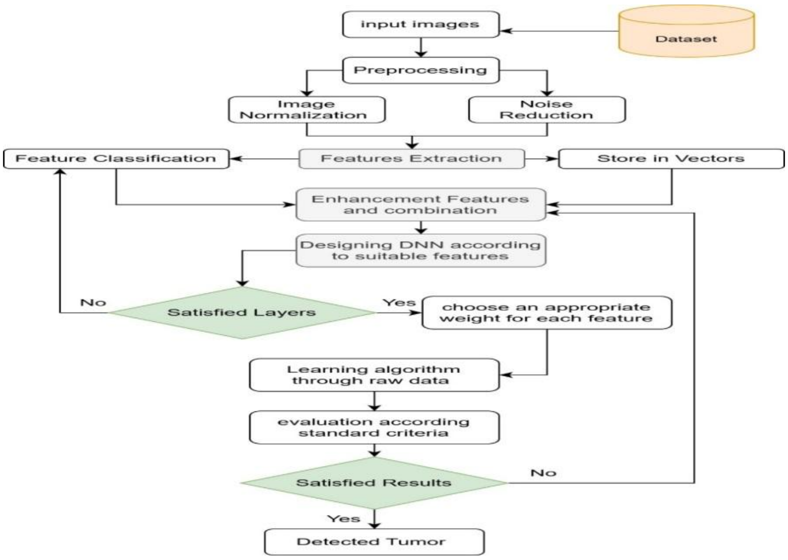

Figure 1. General Framework of the proposed method

Preprocessing can be considered a fundamental step in medical image processing, as it prepares data for a deep learning model and produces high-quality data. These processes include image normalization and noise reduction from the medical devices that extracted the image.

Normalization requires adjusting the values of the medical image to be uniform, which in turn reduces the variance due to acquisition, such as in the scanner, and the variance within the settings.

The new scale of the image in its pixels can be ranged like [0, 1] or [-1, 1]

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \qquad (4)$$

Where: I represent the original image, and the maximum and minimum intensities are I_{max} and I_{min} .

In terms of z-score normalization, the transform intensities of having zero mean or some time variance of the unit can illustrate the normalization as :

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$I_{norm}(x,y) = \frac{I(x,y)-\mu_I}{\sigma_I}$ (5)

Where: μ_I represents the mean of image I intensity, and σ_I represents the standard deviation of image I.

In terms of noise reduction, non-leaner denoising applied, such as the median filter by replacing the pixel with the median of its neighboring pixels, to reduce the salt and pepper noise by:

$$I_{filtered}(x,y) = median\ [I(i,j)]_{(i,j)\in N(x,y),} \qquad (6)$$

Where: $N(x,y)$ consider the local window in the filter of 3×3.

Some noise comes from different devices such as scanners and TVs, denoising, then optimizing the vibrational model to reduce it while maintaining sharp edges:

$$I_{denoised} = \arg\min_{I'}(\|I' - I\|_2^2 + \gamma . TV(I')) \qquad (7)$$

Where: $TV(I')$ represents the total variation (smoothing) and γ strength of regularization.

Then the feature extraction stage begins, features extracted do not necessarily have to be all useful, so we have to determine them as $f = [f_1, f_2, \dots, f_D]$ features in dimension D. Then the features f_i will be relevant to the diagnostic target (classification of target). The discriminative power can be depicted by mutual information, such as $\delta(f_i; y)$, and the robustness represents the variance of the perturbations like $Var(f_i, noise)$, then we can calculate the redundancy by finding the correlation with other features$\rho(f_i, f_j)$. In this case, we can achieve the goal in the feature extraction stage of selecting a subset $\delta \subseteq \{1, \dots, D\}$ to help maximize the performance of diagnosis by :

$\delta^* = \arg\min_{\delta} \mathbb{E}_{(I,y)}[\mathcal{P}(y|\{f_i\}_{i\in\delta})]$ (8)

Where: $\mathcal{P}$ represents the predictive model that helps the performance metric (AUC and accuracy).

For medical images, the challenge is to manipulate small datasets; we can produce limited samples (N) to avoid overfitting in:

$\mathbb{E}[Error\ Generazation] \propto \frac{D}{N}$ (9)

For heterogeneity, the domain can shift according to the feature instability (scanner differences)

$\|f_{scanner\ A} - f_{scanner\ B}\|_2 > \in$ (10)

After feature classification, the optimal feature according to the criteria to satisfy good δ^* in case of satisfying high diagnostic correlation $\max_{i,j\in\delta^*} \mathcal{I}(f_i; y)$, when the correlation between two feature vectors plays an important role in the next stage of designing a neural network.

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Another criterion that can decide the good features is low redundancy, as $\min_{i,j\in\delta^*}\rho(f_i,f_j)$, the features may be redundant with one dataset but become useless in another dataset, so choosing such data should satisfy this criterion.

Other criteria that should be considered are $\min_{i\in\delta^*} Var\,(f_i, |perturbartion)$ to make the feature classification good.

The main goal of the proposed algorithm is to construct an artificial network $\mathcal{F}_{\theta,}$ including the parameters of θ, that helps to extract discriminative features for accurate tumor classification. The features extracted from a certain image (*I*) and input into the neural network, $f^{(0)} = \rho(I)$, are a processed image from the previous stage, normalized, and without noise. Then the initial layer in the neural network is $F^{(1)}$ that contains low-level features such as edge and texture.

$$f^{(1)} = \sigma(W^{(1)} \circledast f^{(0)} + b^{(1)}) \qquad (11)$$

Where: $W^{(1)}$ represents the convolutional filter with detected texture and edge. σ activation function of non-linear. $\circledast$ is considered a convolutional operation. For the other layers in the deep neural network, the hierarchical features are used to capture features of task-specific, such as tumor morphology. If y is considered the target label, then malignant and benign will be detected, and it must ensure that:

$$\mathcal{F}(f^{(L)}; y) \gg \mathcal{F}(f^{(1)}; y) \qquad (12)$$

Where: $\mathcal{F}$ represents the mutual data, L represents how deep the network is. In the training process, it is necessary to learn the feature; increasing the training will increase the robustness of the feature. In the next iteration, the structure of the network will change according to :

$$\min_{\theta}\max_{\|\delta\|\le\in}\gamma(\mathcal{F}_\theta(f+\delta),y) \qquad (13)$$

The contrastive learning of the features is important by pushing similar features into a certain space via:

$$\mathcal{L}_{contrast} = -log\frac{\exp\left(\frac{sim(f_i,f_j)}{\mathcal{T}}\right)}{\sum_{k\neq i}\exp\left(\frac{sim(f_i,f_k)}{\mathcal{T}}\right)} \qquad (14)$$

Where: *sim()* is the function of the similarity metric, such as cosine, f_k is the feature vector in the k domain, then the DNN architecture with combines features during training can be illustrated by :

$$\mathcal{F}_\theta^* = \arg\min_{\mathcal{F}_\theta}(\mathcal{L}_{task} + \lambda_1\mathcal{L}_{sparsity} + \lambda_2\mathcal{L}_{contrast} + \lambda_3\mathcal{L}_{DA}) \qquad (15)$$

Construction with early layers (Gabor like filters, including texture and edge detection), mid layers (including the hierarchical feature learning within iterations), and late layers (representing the final layer with result but with feedback to previous layers).

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At this stage, the learned features can be checked to see if they satisfy a good structure with layers in a neural network, or can be modified. Also depends on the results as explained in detail in the next section.

5.Result and Discussion

In this section, the results of deep learning of the proposed model are clearly explained, and the work is visualized. The proposed model can accurately detect the presence of tumors in medical images with reasonable loss. The sensitivity is not high, but it is considered better in the training phase. In training, the model was able to separate noise and non-brain tissues, and with the overall verification, we can increase the accuracy of the result to better than previous studies, which helps in histological anatomy and surgical work. The work begins by identifying the features of the image that contain the brain and the tumors that are in it. The shape of the tumor, its area, and its image contrast are among the most important features extracted from the image. Each image has specific characteristics that can accurately describe whether it contains tumors or not.

5.1 Model Training

In training mode, the images will run the model according to 80% of the image form dataset and considering the image label. With training, the accuracy will be depicted as a value represented in % with each image. As shown in Figure 2.

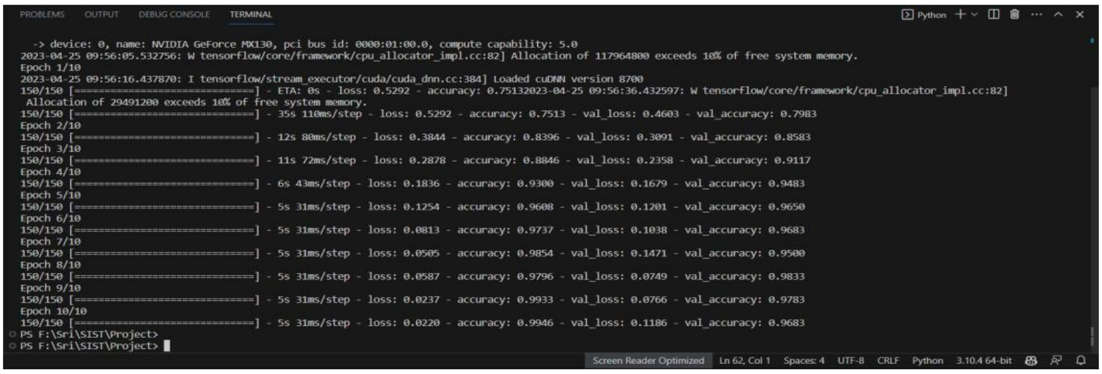

Figure 2. Illustration of Model Training

In Figure 3, it can be confirmed that the accuracy increases with the increase in the number of epochs, and there is a decrease in the loss of the testing set.

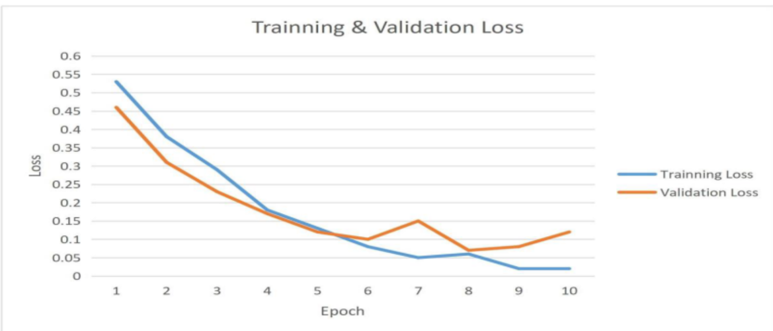

Figure 3. Model Loss

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When the model is applied to the testing data set for 10 epochs, a validation accuracy of 98.33% is obtained, and the validation loss is also lower.

As seen in Figure 4, when the model is applied to the validation, a high loss is obtained, but once applied to the testing set, the loss gradually decreases with the increasing number of epochs.

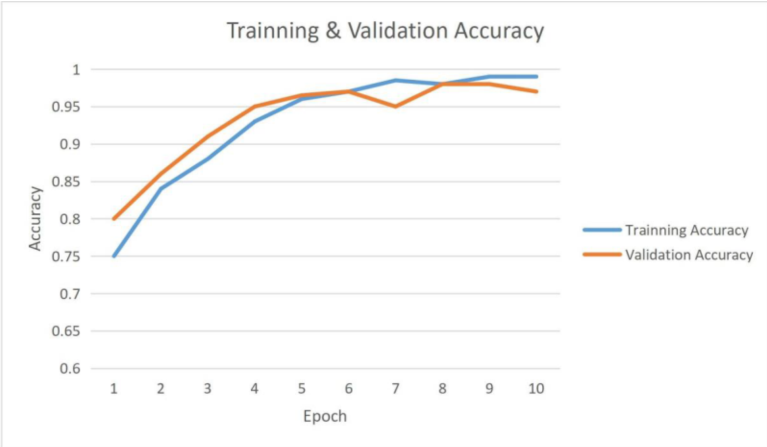

Figure 4. Model Accuracy

The accuracy of the convolutional neural network model achieved after applying it to the testing set was 96.46%. With a very minimal loss, with increasing epochs. The difference in model accuracy can be seen between the validation dataset and the training dataset in Figure 4.

5.2 Model Testing

Testing mode can give the accuracy or predict according to the trained data. Testing mode always runs with the images without a label, so it can depend on the experience of training mode. As shown in Figure 5.

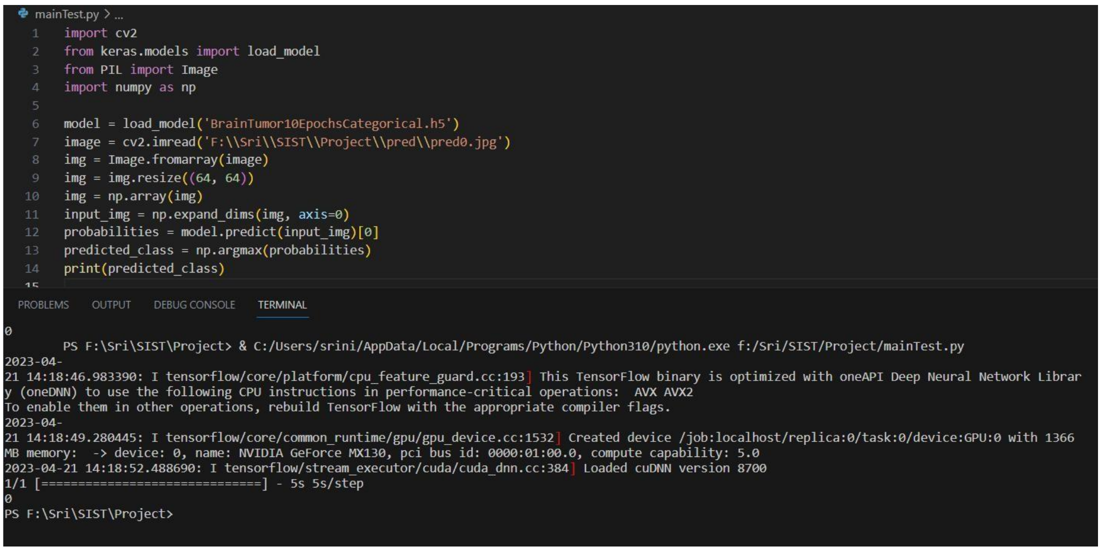

Figure 5. Output of Model Testing

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In this section, learn about the dataset used and its importance for the study in terms of training and testing, in addition to the importance of utilizing influential parameters in the deep neural network. The dataset was chosen appropriately, and the images from historical data come from hospitals and medical institutions. Tumors here differ from one image to another due to the degree of infection, which varies to make the feature extracted more reliable. The dataset of the brain was chosen with a size of 3.8 GB and includes 687000 images for different cases. Only the medical images come from MRI, considered first, and were used in this research, and the dataset files were divided into 70% for training and 30% for testing [42]. As in Figure 6.

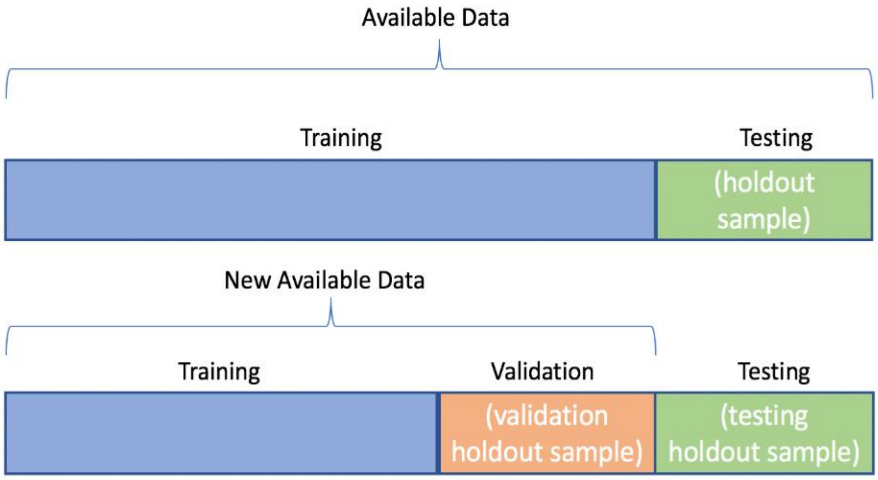

Figure 6. Structure of the dataset in the proposed method

6.Conclusion

This study focuses on extracting useful features in deep learning models for the accurate diagnosis of cancerous tumors in medical images. The method of feature extraction, the learning process, and the multi-scale processing were systematically explored, as well as the feature selection mechanism, which impacts the robustness of the results and clinical applicability. Experimental results confirm that feature selection and extraction are crucial. The removal of features that do not affect the outcome is essential, while retaining features that consistently outperform in accuracy and recall during processing. This is because the model relies on the extracted features, not just the deep learning algorithm. Our study focuses on the differences between medical images and normal images, as processing medical images is a critical task that can be adapted to deep learning algorithms with the ability to extract features. The selected features are aligned with the system's complex ability to detect and classify tumors. In conclusion, we can emphasize that good feature selection is not a secondary feature, but rather a prerequisite for accurate and reliable clinical tumor detection. By following future work and focusing on data mining in deep learning, the importance of its integration with AI technologies and bridging the gap between clinical decisions and the performance of AI algorithms will become clear.

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References

[1] Batool, A., & Byun, Y. C. Brain tumor detection with integrating traditional and computational intelligence approaches across diverse imaging modalities-Challenges and future directions. *Computers in Biology and Medicine*, (2024), 108412; DOI: *10.1016/j.compbiomed.2024.108412*

[2] Khaliki, M. Z., & Başarslan, M. S. Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. *Scientific Reports*, *14*(1), (2024), 2664.

[3] Tan, S. L., Selvachandran, G., Paramesran, R., & Ding, W. Lung cancer detection systems applied to medical images: a state-of-the-art survey. *Archives of Computational Methods in Engineering*, *32*(1), (2025), 343-380.

[4] Manjula, P., Krishnakumar, K., Gl, S., Pandiaraj, S., & Prakash, M. A novel method for detecting liver tumors combining machine learning with medical imaging in ct scans using resunet. In *2024 International Conference on Integrated Circuits and Communication Systems (ICICACS),* (2024, February), (pp. 1-5). IEEE.

[5] Saboor, A., Li, J. P., Ul Haq, A., Shehzad, U., Khan, S., Aotaibi, R. M., & Alajlan, S. A. DDFC: deep learning approach for deep feature extraction and classification of brain tumors using magnetic resonance imaging in E-healthcare system. *Scientific reports*, *14*(1),(2024), 6425.

[6] Sen, A., Maiti, G., Parida, B. K., Mishra, B. P., Arya, M., & Bondar, D. I. Feature Engineering is Not Dead: Reviving Classical Machine Learning with Entropy, HOG, and LBP Feature Fusion for Image Classification. (2025), *arXiv preprint arXiv:2507.13772*.

[7] Endo, T. Analysis of Conventional Feature Learning Algorithms and Advanced Deep Learning Models. *Journal of Robotics Spectrum*, *1*, (2023), 001-012.

[8] Pudjihartono, N., Fadason, T., Kempa-Liehr, A. W., & O'Sullivan, J. M. A review of feature selection methods for machine learning-based disease risk prediction. *Frontiers in bioinformatics*, *2*, (2022) ,927312.

[9] Yao, W., Bai, J., Liao, W., Chen, Y., Liu, M., & Xie, Y. From cnn to transformer: A review of medical image segmentation models. *Journal of Imaging Informatics in Medicine*, *37*(4),(2024), 1529-1547.

[10] Kumar, V., Banerjee, D., Chauhan, R., Kukreti, S., & Gill, K. S. Optimizing skin disease classification: A comprehensive investigation of CNN-SVM hybrid models with layer configurations. In *2024 3rd International Conference for Innovation in Technology (INOCON),* (2024, March), (pp. 1-6). IEEE.

[11] Younesi, A., Ansari, M., Fazli, M., Ejlali, A., Shafique, M., & Henkel, J. A comprehensive survey of convolutions in deep learning: Applications, challenges, and future trends. *IEEE Access*, *12*, (2024), 41180-41218.

[12] Tanaka, M., Ando, T., & Horiuchi, T. Automatic MTF conversion between different characteristics caused by imaging devices. *Journal of Imaging*, *10*(2), (2024), 49.

[13] Raj, A., Pallavi, M. O., & Manoj, N. Development of CheXNet-Based Web Application to Detect Pneumonia Using Chest X-Ray Images. In *2024 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER),*(2024, October),(pp. 322-327). IEEE.

Received: August 09 2025

International Journal of Applied Mathematics

Volume 38 No. 8s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[14] Srinivasan, S., Francis, D., Mathivanan, S. K., Rajadurai, H., Shivahare, B. D., & Shah, M. A. A hybrid deep CNN model for brain tumor image multi-classification. *BMC Medical Imaging*, *24*(1), (2024), 21.

[15] Ye, J., Zhao, Z., Ghafourian, E., Tajally, A., Alkhazaleh, H. A., & Lee, S. Optimizing the topology of convolutional neural network (CNN) and artificial neural network (ANN) for brain tumor diagnosis (BTD) through MRIs. *Heliyon*, *10*(16), (2024).

[16] Heikal, A., El-Ghamry, A., Elmougy, S., & Rashad, M. Z. Fine tuning deep learning models for breast tumor classification. *Scientific Reports*, *14*(1), (2024), 10753.

[17] Nahiduzzaman, M., Abdulrazak, L. F., Kibria, H. B., Khandakar, A., Ayari, M. A., Ahamed, M. F., ... & Kowalski, M. A hybrid explainable model based on advanced machine learning and deep learning models for classifying brain tumors using MRI images. *Scientific Reports*, *15*(1),(2025), 1649.

[18] Kumar, K., & Jyoti, K. Recent Advancements in Grad-CAM and variants: Enhancing Brain Tumor Detection, Segmentation, and Classification.(2024); doi.org/10.21203/rs.3.rs-5485128/v1.

[19] Malkauthekar, M., Gulve, A., & Deshmukh, R. A novel Probabilistic Bi-Level Teaching–Learning-Based Optimization (P-BTLBO) algorithm for hybrid feature extraction and multi-class brain tumor classification using ResNet-50 and GLCM. *Journal of Engineering and Applied Science*, *72*(1), (2025), 103.

[20] Ucar, K. Improving electric vehicle state of charge estimation with wavelet transform-integrated 1D-CNN pooling layers. *Journal of Energy Storage*, *117*, (2025), 116202.

[21] Yang, Z., Zhang, J., Luo, X., Lu, Z., & Shen, L. Medkan: An advanced Kolmogorov-Arnold network for medical image classification. (2025), *arXiv preprint arXiv:2502.18416*.

[22] Kamalov, F., Sulieman, H., Alzaatreh, A., Emarly, M., Chamlal, H., & Safaraliev, M. Mathematical Methods in Feature Selection: A Review. *Mathematics*, *13*(6), (2025), 996.

[23] He, D., Xu, Y., Jin, Z., Liu, Q., Zhao, M., & Chen, Y. A zero-shot model for diagnosing unknown composite faults in train bearings based on label feature vector generated fault features. *Applied Acoustics*, *232*,(2025), 110563.

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