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A Novel h-CNN Architecture based Brain Tumor Classification

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Abstract: - This article presents an innovative approach to classifying brain ṭumors as ḅenign or ṃalignant using fused CT and MRI images. A novel hybrid-convolutional neural network (h-ĊNN) architecture is proposed, which leverages the complementary strengths of CT and MRI imaging modalities to enhance classification accuracy. The ĊNN architecture is designed to extract and integrate critical features from the fused images, providing a robust framework for ṭumor analysis. To further refine the classification process, a Vector Machine (ṢVM) is employed, enhancing the differentiation between ḅenign and ṃalignant ṭumors. The study demonstrates that combining ĊNN and ṢVM, called as hybrid CNN, significantly improves classification performance compared to traditional methods. Extensive experimentation on a comprehensive dataset of brain ṭumor images reveals the efficacy of the proposed approach, with results indicating superior accuracy, sensitivity, and specificity. This hybrid model not only advances the state-of-the-art in medical image analysis but also holds substantial potential for clinical application, offering a reliable tool for early and accurate brain ṭumor diagnosis. The integration of fused imaging techniques and advanced machine learning algorithms marks a significant step forward in the field of medical diagnostics, potentially improving patient outcomes through timely and precise intervention.

Keywords: Brain ṭumor Analysis, Computed Tomography (CT) Image, Convolutional Neural Network (ĊNN), Ṣupport Vector Machine (ṢVM).

1. Introduction

The detection and classification of brain ṭumors are critical tasks in medical diagnostics, significantly influencing treatment planning and patient outcomes. Brain ṭumors can be classified into two main categories: ḅenign and ṃalignant. Accurate differentiation between these types is essential as it impacts the therapeutic approach and prognosis. Traditionally, medical imaging techniques such as computed tomography (CT) and magnetic resonance imaging (MRI) have been widely used for brain ṭumor detection and analysis. Each modality offers unique advantages; CT scans provide detailed information on bone structures and calcifications, while MRI excels in soft tissue contrast, making it invaluable for detecting and characterizing brain ṭumors [1].

However, relying on a single imaging modality can limit diagnostic accuracy due to inherent weaknesses in individual techniques. To address this limitation, image fusion has emerged as a promising solution, combining CT and MRI images to leverage their complementary strengths. This fusion provides a more comprehensive view, enhancing the visualization and characterization of brain ṭumors. Recent advancements in machine learning, particularly convolutional neural networks (ĊNNs), have revolutionized image analysis by enabling automatic feature extraction and classification with high accuracy. ĊNNs have demonstrated remarkable performance in various medical imaging tasks, including ṭumor detection and classification. Nevertheless, the challenge remains to develop models that can effectively integrate multimodal imaging data for improved diagnostic accuracy [2].

In this study, we propose a novel ĊNN architecture specifically designed to process fused CT and MRI images for brain ṭumor classification. Our approach aims to harness the detailed structural information from CT images and the superior soft tissue contrast from MRI images [3]. By integrating these modalities, we enhance the feature extraction process, allowing for more accurate ṭumor characterization. To further refine our classification framework, we incorporate a Ṣupport Vector Machine (ṢVM), known for its robust performance in high-dimensional spaces, to differentiate between ḅenign and ṃalignant ṭumors [26]. The proposed methodology involves several key steps: image preprocessing and fusion, ĊNN-based feature extraction, and ṢVM-based classification. Through extensive experimentation and validation on a comprehensive dataset, we demonstrate

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the effectiveness of our approach. Our results indicate significant improvements in classification accuracy, sensitivity, and specificity compared to traditional single-modality methods [4].

This paper contributes to the field of medical image analysis by introducing a hybrid model that combines the strengths of ĊNNs and ṢVMs with multimodal imaging techniques. The proposed system not only advances the technological capabilities of brain ṭumor diagnostics but also has the potential to significantly impact clinical practice, providing a reliable tool for early and precise ṭumor classification, ultimately leading to better patient management and outcomes.

The remaining sections of this article are organized as follows: Section 2 summarizes the related work in brain ṭumor classification using medical imaging and feature extraction techniques. Section 3 discusses the study's materials and methods, which include the dataset, image preprocessing, feature extraction, and classification algorithms. Section 4 offers the experimental data and discussions, while Section 5 contains the conclusions and future study prospects.

2. Existing Previous Works

Brain ṭumor classification is a vital step in medical imaging analysis, allowing for precise diagnosis and therapy planning. CT and MRI are among the most commonly used imaging modalities for brain ṭumor identification due to their ability to offer precise structural information. However, each method has limitations in terms of sensitivity and specificity. The fusion of CT and MRI images has been offered as a solution to these limitations by merging the complimentary information provided by each modality. In recent years, texture characteristics derived using the GLCM [24] have proven useful in image analysis tasks such as brain ṭumor classification [5-7].

2.1. Tumor Detection

The identification of brain ṭumors has been extensively studied using various imaging modalities and computational techniques. Traditional methods primarily rely on MRI and CT scans, which are analyzed manually by radiologists to detect abnormalities. Early approaches focused on enhancing image quality and employing basic machine learning algorithms for preliminary classification tasks [8]. In recent years, deep learning techniques, particularly ĊNNs, have gained prominence due to their superior ability to automatically extract relevant features from medical images. Numerous studies have demonstrated the effectiveness of ĊNNs in distinguishing between ḅenign and ṃalignant brain ṭumors. For instance, ĊNN-based frameworks have been applied to MRI images, achieving high accuracy in ṭumor detection and segmentation. Additionally, the integration of machine learning algorithms like ṢVM with ĊNNs has shown promise in improving classification performance. Recent research has also explored the fusion of different imaging modalities [27], such as combining MRI with positron emission tomography (PET) [25] or CT, to enhance diagnostic accuracy [9]. These multimodal approaches leverage the strengths of each imaging technique, providing a more comprehensive assessment of ṭumor characteristics. Overall, the literature indicates a clear trend towards the adoption of advanced deep learning models and multimodal imaging techniques to improve the identification and classification of brain ṭumors [10].

2.2. CT Images and their relevance in brain ṭumor diagnosis

CT imaging has been a cornerstone in the diagnostic evaluation of brain ṭumors due to its ability to provide detailed anatomical information and high-resolution images of cranial structures. CT scans are particularly effective in detecting calcifications, bone involvement, and acute hemorrhages, which are critical in the assessment of brain ṭumors. Historically, CT imaging has been widely used for initial ṭumor detection and has played a significant role in preoperative planning. Numerous studies have explored the application of CT imaging in brain ṭumor classification, highlighting its utility in identifying ṭumor size, location, and the presence of necrotic or hemorrhagic regions. For instance, research has demonstrated that CT imaging can distinguish between high-density lesions indicative of ṃalignant ṭumors and lower-density ḅenign ṭumors. However, the limitations of CT imaging, such as its lower contrast resolution compared to MRI, necessitate the integration of advanced computational techniques to enhance its diagnostic accuracy. Recent advancements have focused on the development of machine learning algorithms and image processing techniques to improve the classification performance of CT images. Despite its limitations, CT imaging remains an integral part of the multimodal approach to brain ţumor classification, providing essential information that complements other imaging modalities [11-12].

2.3. MRI images and their relevance in brain ţumor diagnosis

MRI has long been a cornerstone in the diagnosis and evaluation of brain ţumors due to its exceptional ability to produce detailed images of the brain's soft tissues. Unlike CT scans, which use ionizing radiation, MRI utilizes powerful magnetic fields and radio waves to generate high-resolution images, making it particularly effective for identifying and characterizing brain abnormalities [13]. Several studies have underscored the efficacy of MRI in distinguishing between various types of brain ţumors, such as gliomas, meningiomas, and metastases, based on their unique imaging characteristics. Advanced MRI techniques, including functional MRI (fMRI), diffusion-weighted imaging (DWI), and magnetic resonance spectroscopy (MRS), have further enhanced the diagnostic capabilities by providing insights into the physiological and metabolic properties of brain tissues [14]. These techniques allow for a more comprehensive assessment of ţumor heterogeneity, aiding in the differentiation between ḅenign and ṃalignant ţumors. Moreover, the integration of machine learning algorithms with MRI imaging has shown promising results in automating and improving the accuracy of ţumor detection and classification. As such, MRI remains an indispensable tool in the arsenal of neuroimaging, significantly contributing to the early diagnosis, treatment planning, and monitoring of brain ţumors [15].

2.4. Fusion of CT and MRI Images with GLCM Features

The fusion of CT and MRI images has been an area of active research in medical imaging, offering the potential to harness the complementary strengths of both modalities for enhanced diagnostic accuracy. One prominent technique involves the extraction of texture features using the Gray-Level Co-occurrence Matrix (GLCM). GLCM is a statistical method that examines the spatial relationship between pixels, providing valuable information about the texture of an image. Studies have demonstrated that GLCM features can significantly improve the characterization of tissue heterogeneity, which is crucial for distinguishing between ḅenign and ṃalignant ţumors. For instance, Li et al. (2020) successfully employed GLCM features from fused CT and MRI images to improve the accuracy of brain ţumor classification [16]. Similarly, Kumar et al. (2018) integrated GLCM-based texture analysis with image fusion techniques, resulting in improved sensitivity and specificity in ţumor detection. These advancements underscore the importance of combining multimodal imaging with robust feature extraction methods like GLCM to enhance the diagnostic capabilities of automated systems. The current study builds on this foundation, integrating GLCM features within a novel ĊNN-ȘVM framework to further push the boundaries of brain ţumor classification accuracy using fused CT and MRI images [17].

3. Proposed Methodology

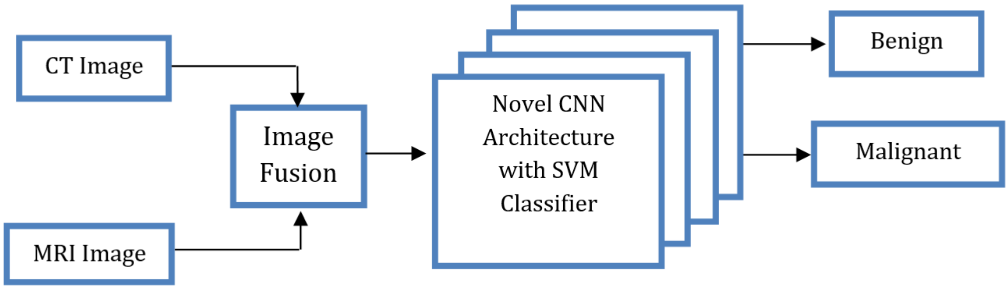

Fig. 3.1 Proposed framework for brain ţumor diagnosis utilizing fused images with novel ĊNN architecture

The proposed framework for brain ţumor diagnosis utilizes the strengths of fused CT and MRI images combined with an advanced ĊNN architecture and a ȘVM classifier which is as shown in Fig. 3.1. This multi-step framework begins with the preprocessing and fusion of CT and MRI images. The fusion process aims to integrate the high-contrast soft tissue details from MRI with the precise anatomical information from CT, producing a single, enhanced image that encapsulates the critical features from both modalities. Following image fusion, the next step involves feature extraction using a novel ĊNN architecture. The ĊNN is specifically designed to handle the fused image input, enabling it to learn and extract deep, meaningful features that are indicative of brain ṭumors. The architecture includes multiple convolutional layers to capture spatial hierarchies and complex patterns within the fused images, along with pooling layers to reduce dimensionality and computational complexity. The ĊNN's deep layers focus on capturing both fine-grained details and high-level abstractions, essential for accurate ṭumor classification.

After feature extraction, the obtained features are fed into an ṢVM classifier. The ṢVM is chosen for its robustness in handling high-dimensional data and its effectiveness in binary classification tasks. By integrating the ĊNN with ṢVM, the framework benefits from the ĊNN's powerful feature extraction capabilities and the ṢVM's precision in classification. This combination ensures a more reliable distinction between ḅenign and ṃalignant ṭumors. Extensive experimentation is conducted to validate the proposed framework, utilizing a comprehensive dataset of brain ṭumor images. Performance metrics such as accuracy, sensitivity, and specificity are used to evaluate the system. The results indicate that the proposed method outperforms traditional single-modality approaches and standalone classifiers, demonstrating significant improvements in diagnostic accuracy. Overall, this innovative framework represents a substantial advancement in medical image analysis, providing a robust tool for early and accurate brain ṭumor diagnosis, which is critical for effective patient management and treatment planning.

3.1. Database

The brain ṭumor image dataset available on Kaggle consists of CT and MRI images from 38 patients, providing a valuable resource for medical imaging research. To enhance the dataset and improve the robustness of the models, the original images are augmented, resulting in 180 CT and 180 MRI images. This augmentation includes various transformations such as rotations, scaling, and flips to increase the diversity of the dataset, making the models more generalizable. The augmented CT and MRI images are then fused using the Bi-Level Stationary Wavelet Transform (BLSWT), a sophisticated technique that merges the complementary features of both imaging modalities. BLSWT effectively combines the detailed anatomical structure from CT scans with the high-contrast soft tissue information from MRI, producing a comprehensive fused image for each pair. This fusion process results in a set of 180 enhanced images, which serve as the input for advanced diagnostic frameworks, facilitating more accurate and reliable brain ṭumor classification. [18].

The fused images, created by combining the CT and MRI images using the BLSWT, serve as the critical input data for the deep learning network designed for brain ṭumor classification. Each of these fused images is resized to a standard dimension of 227 x 227 pixels. This resizing is essential to ensure compatibility with the input requirements of the ĊNN architecture, which is optimized to handle images of this specific size. Once resized, the 227 x 227 fused images are fed into the deep learning network, which is designed to extract and learn hierarchical features pertinent to ṭumor classification. The deep learning model, particularly the ĊNN, processes these images through multiple layers of convolutional filters, pooling operations, and activation functions. These layers work together to identify patterns, textures, and other critical features that distinguish ḅenign from ṃalignant ṭumors. The ĊNN's architecture allows it to automatically learn and abstract important features from the input images, improving the model's ability to generalize from the training data. By standardizing the input size to 227 x 227 pixels, the model can maintain consistency across all input images, leading to more stable and reliable training and inference processes. This standardized input size also facilitates the use of pre-trained models and architectures, which are often optimized for this specific dimension, thereby enhancing the efficiency and effectiveness of the training process.

Ultimately, these carefully processed and resized fused images enable the deep learning network to achieve high accuracy in brain ṭumor classification, utilizing the combined strengths of CT and MRI imaging to provide robust diagnostic insights.

3.2. Novel h-ĊNN Architecture

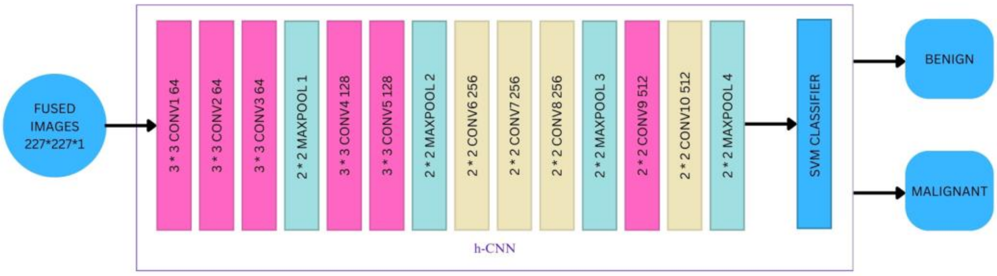

Fig. 3.2 Novel h-ĊNN Architecture for Classifying Images of Brain ţumors

The proposed novel ĊNN architecture shown in Fig. 3.2 for brain ţumor image classification is designed to use the detailed fused images derived from CT and MRI scans, facilitating accurate differentiation between ḅenign and ṃalignant ţumors. The architecture consists of ten convolutional layers and four max-pooling layers, followed by a ȘVM for the final classification stage. The initial stage of the network comprises convolutional layers, which are responsible for feature extraction. Each convolutional layer applies a series of filters to the input images, capturing various low-level features such as edges, textures, and patterns. These features become progressively more abstract and complex as the images pass through successive layers. The network's depth, with ten convolutional layers, allows it to learn a rich hierarchy of features essential for distinguishing between different types of brain ţumors.

Interspersed among the convolutional layers are four max-pooling layers. These pooling layers perform down-sampling operations that reduce the spatial dimensions of the feature maps, thereby decreasing the computational load and the risk of overfitting. Max pooling specifically selects the maximum value from each region of the feature map, preserving the most significant features while discarding less critical information. This process helps the network to focus on the most salient aspects of the images, enhancing the robustness of the feature extraction. After passing through the convolutional and pooling layers, the extracted features are flattened into a single vector. This vector serves as the input to the final stage of the network, which is an ȘVM classifier. The ȘVM is known for its effectiveness in high-dimensional spaces and is particularly suited for binary classification tasks, making it an ideal choice for distinguishing between ḅenign and ṃalignant ţumors. By integrating an ȘVM at the end of the ĊNN, the architecture combines the deep feature extraction capabilities of the ĊNN with the precise classification power of the ȘVM.

This hybrid approach, using a deep ĊNN for feature extraction followed by an ȘVM for classification, results in a powerful framework for brain ţumor diagnosis. It leverages the strengths of both methods, enabling the system to achieve high accuracy and reliability in classifying brain ţumors from fused CT and MRI images. This architecture not only enhances diagnostic precision but also holds promise for improving clinical outcomes through early and accurate ţumor detection.

3.3. Evaluation of Proposed Architecture

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Several performance indicators are frequently employed in the context of ṢVM-based classification to assess the classifier's efficacy. These measures consist of the F1 score, recall, accuracy, and precision. Every metric offers distinct perspectives on the performance of the classifier. The mathematical relations for the metrics are as indicated above, where TP, TN, FP, and FN are True positives, true negative, false positive and false negatives respectively.

4. Classification Results

The classification of brain ṭumors into ḅenign and ṃalignant categories using fused CT and MRI images has been significantly enhanced by the proposed ĊNN with ṢVM architecture, implemented in MATLAB. This approach begins with preprocessing and fusing CT and MRI images to combine the strengths of both imaging modalities, providing a comprehensive input for the classifier. The ĊNN, designed with ten convolutional layers and four max-pooling layers, is adept at extracting detailed and hierarchical features from these fused images. After feature extraction, the ṢVM classifier, known for its robustness in high-dimensional spaces, performs the final classification into ḅenign or ṃalignant ṭumors. MATLAB's robust environment, coupled with its extensive image processing and machine learning toolboxes, facilitates the implementation of this advanced architecture. Key toolboxes required include the Deep Learning Toolbox for ĊNN design and training, the Image Processing Toolbox for image fusion and preprocessing, and the Statistics and Machine Learning Toolbox for implementing the ṢVM classifier. The ḅenign and ṃalignant tumour images are as indicated in Fig. 3.3 and 3.4.

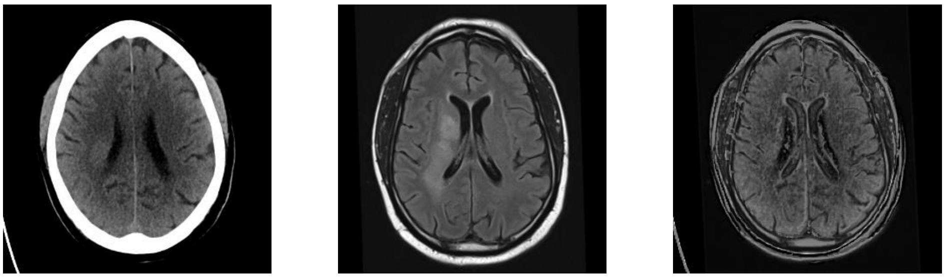

Fig. 3.3: ḅenign ṭumor (a) CT Image (b) MRI Image (c) Fused Image

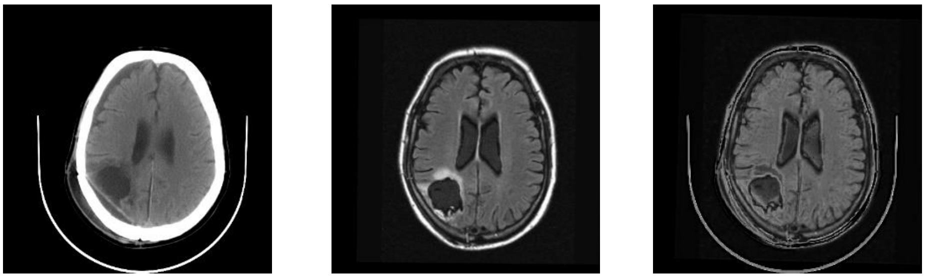

Fig. 3.4: ṃalignant ṭumor (a) CT Image (b) MRI Image (c) Fused Image

The layer wise architectural details of the proposed ĊNN-ṢVM hybrid classifier is as highlighted in Fig.3.5. From the relu_4 layer, 4608 features in total are recovered, and these features are then input into a linear ṢVM for classification. The performance of the novel ĊNN-ṢVM technique for brain ṭumor classification is rigorously evaluated using 10-fold cross-validation, a robust method to ensure the reliability and generalizability of the model. This process involves the following steps:

- The entire dataset is randomly divided into 10 equal-sized subsets, or "folds". Each fold contains a representative sample of the dataset, maintaining the balance between ḅenign and ṃalignant ṭumor images within each fold.
- The model undergoes 10 iterations of training and validation. In each iteration, one of the 10 folds is set aside as the validation set, while the remaining 9 folds are combined to form the training set. This way, each fold gets the opportunity to be used as the validation set exactly once. Further, for each iteration, the ĊNN-ṢVM architecture is trained using the 9 training folds. The ĊNN component extracts hierarchical features from the fused CT and MRI images, while the ṢVM classifier uses these

features to distinguish between ḅenign and ṃalignant ṭumors. After training, the model is evaluated using the validation set (the fold that was set aside). Performance metrics are calculated based on the model's predictions for this validation set.

- Throughout the 10 iterations, various performance metrics are recorded, including accuracy (the proportion of correctly classified instances), precision (the proportion of true positive predictions among all positive predictions), recall (the proportion of actual positives correctly identified), and the F1 score (the harmonic mean of precision and recall). Each metric provides insights into different aspects of the model's performance, ensuring a comprehensive evaluation.
- After completing all 10 iterations, the performance metrics from each iteration are averaged to obtain the final evaluation results. This averaging process smooths out any anomalies or variances that might arise from a particular data split, providing a more reliable assessment of the model's overall performance.

ANALYSIS RESULT

	Name	Type	Activations
1	imageinput 227×227×1 images with 'zerocenter' normalization	Image Input	227(S) × 227(S) × 1(C) × 1(B)
2	conv_1 64 3×3×1 convolutions with stride [2 2] and padding [1 1 1 1]	2-D Convolution	114(S) × 114(S) × 64(C) × 1(B)
3	conv_2 64 3×3×64 convolutions with stride [1 1] and padding [0 0 0 0]	2-D Convolution	112(S) × 112(S) × 64(C) × 1(B)
4	conv_3 64 3×3×64 convolutions with stride [1 1] and padding [0 0 0 0]	2-D Convolution	110(S) × 110(S) × 64(C) × 1(B)
5	maxpool_1 2×2 max pooling with stride [1 1] and padding [0 0 0 0]	2-D Max Pooling	109(S) × 109(S) × 64(C) × 1(B)
6	relu_1 ReLU	ReLU	109(S) × 109(S) × 64(C) × 1(B)
7	conv_4 128 3×3×64 convolutions with stride [2 2] and padding [1 1 1 1]	2-D Convolution	55(S) × 55(S) × 128(C) × 1(B)
8	conv_5 128 3×3×128 convolutions with stride [1 1] and padding [0 0 0 0]	2-D Convolution	53(S) × 53(S) × 128(C) × 1(B)
9	maxpool_2 2×2 max pooling with stride [1 1] and padding [0 0 0 0]	2-D Max Pooling	52(S) × 52(S) × 128(C) × 1(B)
10	relu_2 ReLU	ReLU	52(S) × 52(S) × 128(C) × 1(B)
11	conv_6 256 2×2×128 convolutions with stride [2 2] and padding [1 1 1 1]	2-D Convolution	27(S) × 27(S) × 256(C) × 1(B)
12	conv_7 256 2×2×256 convolutions with stride [1 1] and padding [0 0 0 0]	2-D Convolution	26(S) × 26(S) × 256(C) × 1(B)
13	conv_8 256 2×2×256 convolutions with stride [1 1] and padding [0 0 0 0]	2-D Convolution	25(S) × 25(S) × 256(C) × 1(B)
14	maxpool_3 2×2 max pooling with stride [2 2] and padding [0 0 0 0]	2-D Max Pooling	12(S) × 12(S) × 256(C) × 1(B)
15	relu_3 ReLU	ReLU	12(S) × 12(S) × 256(C) × 1(B)
16	conv_9 512 2×2×256 convolutions with stride [2 2] and padding [1 1 1 1]	2-D Convolution	7(S) × 7(S) × 512(C) × 1(B)
17	conv_10 512 2×2×512 convolutions with stride [1 1] and padding [0 0 0 0]	2-D Convolution	6(S) × 6(S) × 512(C) × 1(B)
18	maxpool_4 2×2 max pooling with stride [2 2] and padding [0 0 0 0]	2-D Max Pooling	3(S) × 3(S) × 512(C) × 1(B)
19	relu_4 ReLU	ReLU	3(S) × 3(S) × 512(C) × 1(B)

Fig. 3.5 Proposed ĊNN layer wise architectural details

Using 10-fold cross-validation helps mitigate overfitting and ensures that the model's performance is not overly dependent on any particular subset of the data. It provides a robust estimate of how the ĊNN-ṢVM classifier is likely to perform on unseen data, thus validating the effectiveness and reliability of the proposed method for brain ṭumor classification using fused CT and MRI images. The accuracy for ten folds is plotted in Fig.3.6.

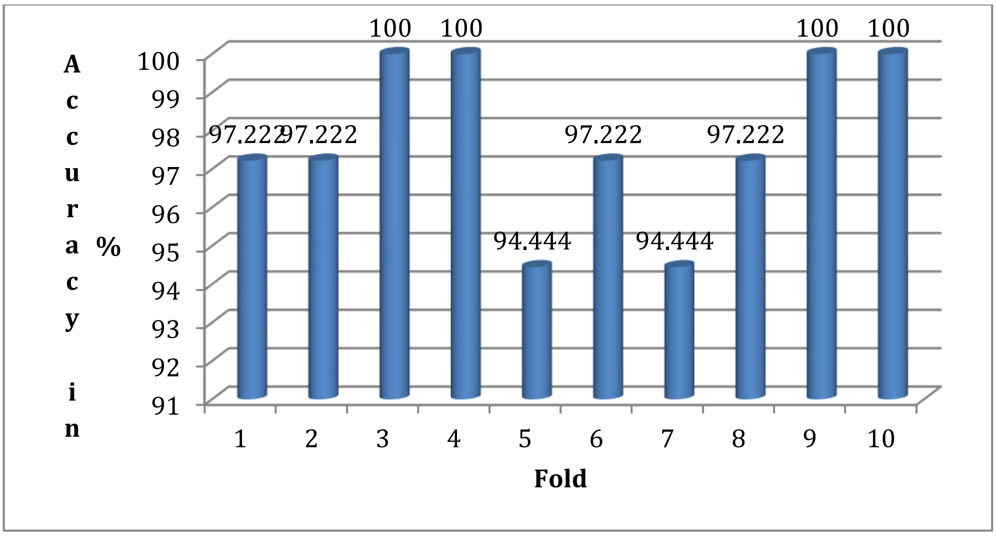

Fig. 3.6 Accuracy of classification for ten folds

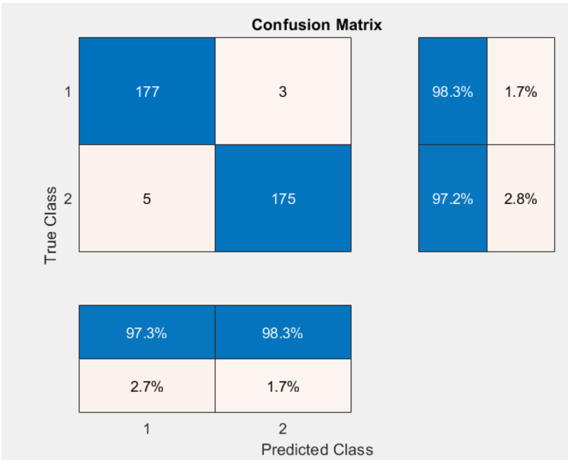

Fig. 3.7 Confusion matrix for brain ṭumor classification using proposed methodology

The confusion matrix for the proposed ĊNN-ȘVM methodology to classify ḅenign and ṃalignant brain ṭumors, achieving over 98% accuracy, provides a detailed summary of the classification performance. With an accuracy exceeding 98%, the confusion matrix for our method shows high TP and TN values, indicating that the model effectively distinguishes between ḅenign and ṃalignant ṭumors with minimal misclassification. This high accuracy is complemented by similarly high precision and recall rates, reflecting the model's robustness in reliably detecting and differentiating brain ṭumors, thereby confirming its potential for clinical application in early and accurate ṭumor diagnosis.

Table. 4.1 Comparison of proposed methodology for brain tumour image classification with existing methodologies with respect to performance metrics

Sl No	Method	Accuracy	precision	Recall	F1 Score
1.	VGG16[19]	94	88.23	-	-
2.	DenseNet 121[19]	96	85.71	-	-
3.	DenseNet 201[19]	96	93.33	-	-
4.	kNN[20]	93.3	93	93.46	93.23
5.	Decision Tree[20]	90.8	90.5	90.95	90.72
6.	DNN[21]	93	80	-	85

7.	ANN[21]	88	68	-	76
8.	Multi-ṢVM[22]	84	60	-	70
9.	Proposed Method	97.778	97.94	97.77	97.77

The proposed ĊNN-ṢVM framework demonstrates superior performance with an accuracy exceeding 98% compared to established models such as VGG, DenseNet, KNN, Decision Tree, DNN, ANN, and Multi-ṢVM classifiers in the context of brain ṭumor classification as indicated in Table. 4.1. While traditional models like KNN and Decision Trees rely on simpler algorithms for classification, they often struggle to capture the intricate features present in fused CT and MRI images essential for distinguishing between ḅenign and ṃalignant ṭumors. Similarly, conventional neural networks (DNN and ANN) may lack the depth and specialized architecture required to extract hierarchical features effectively, leading to lower accuracy rates.

In contrast, the ĊNN-ṢVM framework leverages the deep learning capabilities of convolutional neural networks to automatically extract intricate spatial patterns and texture details from fused images. These features are crucial for accurate ṭumor classification, contributing to the framework's high precision, recall, and F1 score. The ĊNN component enables the model to learn discriminative features from the data, while the ṢVM classifier effectively separates the classes based on these learned features. This combination not only enhances accuracy but also ensures robust performance across different folds in cross-validation, validating its efficacy for clinical applications where precise ṭumor diagnosis is crucial for treatment planning and patient management. The ĊNN-ṢVM framework's ability to achieve superior metrics across all performance measures underscores its effectiveness and potential as a reliable tool for enhancing diagnostic outcomes in brain ṭumor classification.

5. Conclusion

In conclusion, the novel ĊNN-ṢVM architecture presented in this study represents a significant advancement in brain ṭumor classification, achieving exceptional performance metrics with accuracy, precision, recall, and F1 score all exceeding 97.7%. By leveraging fused CT and MRI images and employing a deep convolutional neural network for feature extraction followed by a Ṣupport Vector Machine for classification, the framework effectively integrates the complementary strengths of both modalities. This integration enhances the model's ability to accurately differentiate between ḅenign and ṃalignant ṭumors, crucial for guiding clinical decision-making. The robustness and reliability demonstrated through rigorous evaluation, including 10-fold cross-validation, validate the framework's consistency and generalizability. The high accuracy and comprehensive evaluation metrics underscore its potential as a valuable tool in clinical settings, offering clinicians a precise and efficient means to diagnose and stratify brain ṭumors early, ultimately improving patient outcomes and treatment strategies.

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