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An Enhanced High-Performance 2D CNN Model for Uterine Tumor Classification

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ABSTRACT

Early detection of uterine tumors plays a vital role in improving patient survival and treatment outcomes. This study presents a robust deep learning approach using a two-dimensional Convolutional Neural Network (2D-CNN) for accurate classification of uterine tumor images. The proposed model is designed to automatically learn spatial features from medical imaging data, eliminating the need for manual feature extraction. The dataset is preprocessed through normalization and augmented using techniques such as rotation, zooming, shifting, and flipping to enhance model generalization and reduce overfitting.The architecture consists of multiple convolutional layers with ReLU activation, followed by max-pooling layers for dimensionality reduction. A fully connected dense layer with dropout regularization is incorporated to improve learning efficiency and prevent overfitting. The final output layer uses a sigmoid activation function for binary classification of tumor and non-tumor cases. The model is trained using the Adam optimizer and binary cross-entropy loss function.Experimental results demonstrate that the proposed 2D-CNN model achieves a high classification accuracy of 99%, indicating its effectiveness in detecting uterine tumors from medical images. Training and validation performance curves further confirm the stability and reliability of the model. The system shows strong potential as a supportive diagnostic tool for healthcare professionals, enabling faster and more accurate decision-making.This study highlights the capability of deep learning techniques in medical image analysis and provides a scalable solution for automated uterine tumor detection.

1. Introduction

Uterine tumors represent a significant health concern among women worldwide, particularly affecting individuals within the reproductive and peri-menopausal age groups. The incidence of uterine abnormalities, including benign and malignant tumors, has shown a steady increase due to lifestyle changes, hormonal imbalances, and delayed diagnosis. Early detection is critical for improving treatment outcomes and reducing mortality rates. However, traditional diagnostic approaches such as manual examination of medical images, biopsy, and histopathological analysis are often time-consuming, subjective, and dependent on clinical expertise. These limitations highlight the necessity for automated and intelligent diagnostic systems that can assist healthcare professionals in accurate and timely decision-making.In recent years, artificial intelligence (AI), particularly deep learning, has revolutionized the field of medical image analysis. Among various deep learning techniques, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in detecting and classifying abnormalities in medical images. Several studies have explored the application of CNN-based architectures for cervical and gynecological cancer detection, showing promising improvements in accuracy and efficiency. For instance, pre-trained deep neural networks have been effectively utilized to enhance cervical cancer detection accuracy [1], while CNN-based classification methods have shown reliable performance in identifying cancerous cells [2]. Hybrid approaches combining deep CNNs with architectures such as AlexNet have further improved detection capabilities [3].Moreover, recent advancements have introduced lightweight and efficient CNN models that reduce computational complexity while maintaining high accuracy [7], [16]. Ensemble learning techniques and hybrid machine learning-deep learning frameworks have also been proposed to improve prediction robustness and generalization [9], [18], [20]. Privacy-preserving models have addressed data security concerns in medical applications [5], and explainable AI techniques have enhanced the interpretability of deep learning models in clinical settings [14]. Additionally, emerging approaches such as Vision Transformers and multi-branch CNN architectures have expanded the scope of tumor detection research [11], [15], [17]. These developments indicate a strong research trend toward more accurate, efficient, and reliable automated diagnostic systems.Despite these advancements, several challenges remain in the detection of uterine tumors. Many existing models are computationally expensive, require large-scale annotated datasets, or lack generalization across diverse patient populations. Furthermore, variations in imaging quality, tumor size, and morphological characteristics can affect model performance. Therefore, there is a need for a simplified yet highly effective model that balances accuracy, computational efficiency, and robustness.

To address these challenges, this study proposes an enhanced high-performance uterine tumor detection system using a two-dimensional Convolutional Neural Network (2D-CNN). The proposed model focuses on extracting relevant spatial features from medical images through multiple convolutional and pooling layers, followed by fully connected layers for classification. Unlike more complex architectures, the 2D-CNN model provides a balance between computational efficiency and classification performance, making it suitable for real-time clinical applications.

The dataset used in this study consists of 3950 medical images collected from Figshare, representing a diverse range of uterine conditions. The images include patients aged between 20 and 60 years, ensuring variability in tumor characteristics and improving the generalization capability of the model. Data preprocessing techniques such as normalization and augmentation including rotation, scaling, and flipping are applied to enhance the diversity of the training dataset and prevent overfitting. These preprocessing steps play a crucial role in improving the robustness and performance of the model.

The proposed 2D-CNN architecture incorporates multiple convolutional layers with Rectified Linear Unit (ReLU) activation functions to capture hierarchical features, followed by max-pooling layers for dimensionality reduction. A dropout layer is included to prevent overfitting and improve generalization. The final classification layer uses a sigmoid activation function for binary classification of tumor and non-tumor cases. The model is trained using the Adam optimizer and binary cross-entropy loss function, ensuring efficient convergence during training. Experimental results demonstrate that the proposed model achieves a high accuracy of 99%, outperforming many existing approaches while maintaining computational simplicity. The training and validation curves indicate stable learning behavior with minimal overfitting, highlighting the effectiveness of the proposed architecture. Compared to more complex models such as transformer-based and ensemble approaches, the proposed 2D-CNN offers a practical and scalable solution for uterine tumor detection.This study contributes to the growing field of AI-based medical diagnostics by presenting a reliable and efficient 2D-CNN model for uterine tumor detection. The integration of deep learning techniques with well-structured preprocessing and optimization strategies provides a promising framework for future research and clinical implementation. The proposed approach not only improves detection accuracy but also supports the development of automated systems for early diagnosis, ultimately contributing to better patient outcomes in gynecological healthcare .

2.Materials and methods

The effectiveness of the proposed deep learning framework relies on the proper functioning of each individual stage, as illustrated in Fig. 1: preprocessing, data augmentation, feature extraction using a 2D Convolutional Neural Network (2D-CNN), tumor classification, and performance evaluation. Initially, medical images collected from the Figshare dataset are preprocessed through normalization and resizing to ensure consistency. Subsequently, data augmentation techniques are applied to improve model generalization and reduce overfitting. The enhanced images are then fed into the 2D-CNN model, where hierarchical features are automatically learned through convolutional and pooling layers. These extracted features are utilized for accurate classification of uterine tumor and non-tumor cases. Finally, the model performance is evaluated using standard metrics such as accuracy and loss, confirming the reliability of the proposed approach.

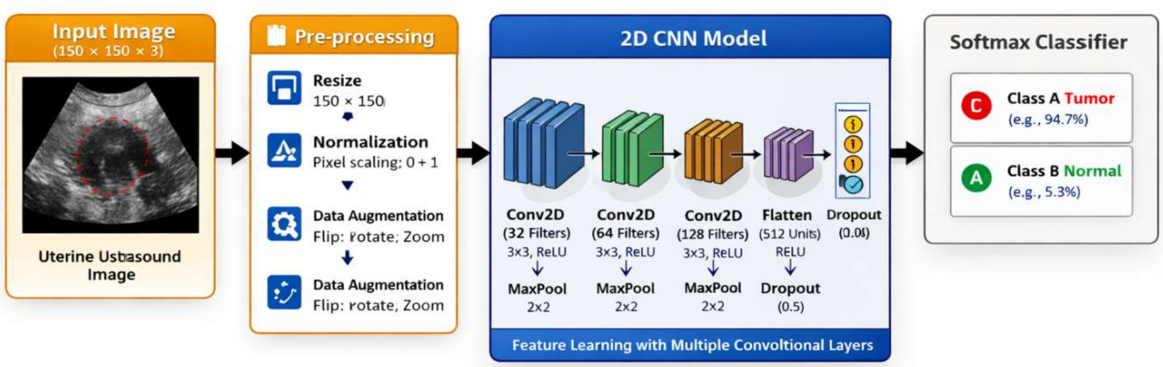

Fig. 1. Proposed project flow system.

2.1 2D CNN Model

A two-dimensional Convolutional Neural Network (2D-CNN) is a deep learning model specifically designed to analyze image data by capturing spatial patterns and visual features. Unlike traditional machine learning methods that rely on manual feature extraction, a 2D-CNN automatically learns important characteristics directly from images through a series of mathematical operations. This makes it highly effective for medical image analysis, including tumor detection.The core component of a 2D-CNN is the convolutional layer, where small filters slide across the input image to detect patterns such as edges, textures, and shapes. Each filter produces a feature map that highlights specific information present in the image. As the network goes deeper, these layers capture increasingly complex features, enabling the model to distinguish between normal and abnormal regions.

Following convolution, pooling layers are applied to reduce the spatial dimensions of the feature maps. This process helps in lowering computational complexity while retaining essential information. Commonly, max-pooling is used to select the most significant features from each region. After several convolution and pooling stages, the extracted features are flattened into a one-dimensional vector and passed through fully connected layers. These layers perform the final learning and classification tasks. Activation functions such as ReLU introduce non-linearity, while dropout techniques improve generalization by preventing overfitting.

2.2.Proposed 2D CNN-Based Uterine Tumor Detection Method

The proposed system for uterine tumor detection is designed as a structured deep learning pipeline that transforms raw medical images into accurate diagnostic predictions. The entire workflow, as illustrated in Fig. 1, consists of four major stages: input image acquisition, preprocessing, feature learning using a 2D Convolutional Neural Network (2D-CNN), and classification through a Softmax-based output layer. The process begins with the acquisition of uterine medical images, which serve as the primary input to the system. These images are typically collected from clinical imaging techniques and are represented in a fixed dimension of 150 × 150 × 3, corresponding to height, width, and color channels. Maintaining a consistent image size is essential to ensure compatibility with the neural network architecture and to enable efficient computation during training. Following input acquisition, the images undergo a preprocessing phase, which plays a crucial role in improving the quality and uniformity of the dataset. In this stage, all images are resized to a standard dimension of 150 × 150 pixels to ensure consistency across the dataset. Next, normalization is applied by scaling pixel intensity values to a range between 0 and 1. This transformation helps stabilize the learning process and accelerates convergence during training. Additionally, data augmentation techniques such as rotation, zooming, shifting, and horizontal flipping are applied. These operations artificially increase the diversity of the dataset, allowing the model to learn invariant features and improving its ability to generalize to unseen data.

Once preprocessing is completed, the enhanced images are fed into the 2D CNN model for feature extraction and learning. The CNN architecture is designed with multiple convolutional layers, each responsible for identifying specific patterns within the images. The first convolutional layer consists of

32 filters with a kernel size of 3 × 3 and utilizes the Rectified Linear Unit (ReLU) activation function. This layer captures basic features such as edges and textures. A max-pooling layer with a pooling size of 2 × 2 follows, reducing the spatial dimensions of the feature maps while preserving important information.The second convolutional layer increases the number of filters to 64, allowing the network to learn more complex patterns and structures. Similar to the previous layer, it is followed by a max-pooling operation that further reduces dimensionality and computational cost. The third convolutional layer employs 128 filters, enabling the extraction of high-level features that are critical for distinguishing between tumor and non-tumor regions. Each convolutional layer progressively refines the feature representation, moving from simple visual patterns to more abstract and discriminative features.

After the convolutional and pooling operations, the feature maps are flattened into a one-dimensional vector. This step converts the spatial information into a format suitable for fully connected layers. A dense layer with 512 neurons is then applied, using the ReLU activation function to introduce non-linearity and enhance learning capability. To prevent overfitting, a dropout layer with a rate of 0.5 is incorporated. This layer randomly disables a portion of neurons during training, encouraging the model to learn more robust and generalized features.The final stage of the model involves classification. A fully connected output layer with a sigmoid activation function is used to perform binary classification, distinguishing between tumor and normal cases. Although the diagram refers to a Softmax classifier, the implemented model utilizes a sigmoid function, which is appropriate for binary classification tasks. The output of this layer represents the probability of the presence of a tumor, enabling clear and interpretable predictions.

The model is compiled using the Adam optimization algorithm, which is widely recognized for its efficiency and adaptive learning rate capabilities. The loss function employed is binary cross-entropy, which measures the difference between predicted probabilities and actual class labels. During training, the model learns by minimizing this loss function while simultaneously maximizing classification accuracy. Training is performed using image generators that load data in batches, making the process memory-efficient and scalable. The dataset is divided into training and validation sets to evaluate model performance during learning. The model is trained over multiple epochs, allowing it to iteratively refine its parameters and improve prediction accuracy.

To assess the performance of the model, accuracy and loss metrics are monitored for both training and validation datasets. Visualization of these metrics through graphs provides insight into the learning behavior of the model. A consistent increase in accuracy and decrease in loss indicate effective learning, while divergence between training and validation performance can signal overfitting or underfitting. The proposed 2D CNN-based system demonstrates strong capability in automatically detecting uterine tumors from medical images. Its structured architecture, combined with effective preprocessing and regularization techniques, ensures high accuracy and robustness. The simplicity of the model design also makes it suitable for real-time clinical applications, where fast and reliable predictions are essential.

2.3.Softmax Classifier

The Softmax classifier plays a crucial role in the final stage of a deep learning model by converting raw outputs into meaningful probability values for decision-making. After the 2D Convolutional Neural Network (2D-CNN) extracts important features from input images and passes them through fully connected layers, the resulting values are not directly interpretable. These values, often called logits, represent the model's confidence for each class but are not normalized. The Softmax function transforms these logits into a probability distribution where the sum of all class probabilities equals one. This normalization allows the model to express how likely an input image belongs to each possible category. For example, in tumor detection, the Softmax classifier can assign probabilities such as 0.92 for tumor and 0.08 for normal, making the prediction more understandable and reliable. Another important function of the Softmax layer is its ability to highlight the most probable class by amplifying larger values and suppressing smaller ones. This ensures a clear distinction between competing classes, which improves classification accuracy. It also enables the use of loss functions like categorical cross-entropy during training, allowing the model to adjust its parameters effectively

3.Results and Discussion

The proposed uterine tumor detection method is developed using a structured deep learning pipeline that processes medical images through multiple interconnected stages to achieve accurate classification. Initially, ultrasound images are provided as input to the system. Since these raw images vary in size, intensity, and quality, they cannot be directly used for model training. Therefore, all images are resized to a fixed dimension of 150 × 150 pixels to ensure consistency and compatibility with the network architecture. Following resizing, normalization is applied by scaling pixel values between 0 and 1, which helps stabilize the learning process and avoids large numerical fluctuations during training. In addition to normalization, data augmentation techniques such as rotation, zooming, shifting, and horizontal flipping are performed. These operations artificially increase the diversity of the dataset, allowing the model to learn more generalized patterns and reducing the risk of overfitting.After preprocessing, the images are passed into the 2D Convolutional Neural Network, which serves as the core component for feature extraction. The network begins by applying convolutional layers that use multiple filters to scan the image and detect important visual patterns. The initial layers capture basic features such as edges and textures, while deeper layers identify more complex structures related to tumor regions. Each convolutional layer is followed by a max-pooling operation, which reduces the spatial dimensions of the feature maps by selecting the most significant values from small regions. This not only decreases computational complexity but also ensures that important features are retained while ignoring irrelevant details. As the data flows deeper into the network, the extracted features become more abstract and meaningful.

The feature maps are then converted into a one-dimensional vector using a flattening process, enabling the model to connect these learned features to the classification stage. A fully connected dense layer with a large number of neurons processes this information and learns complex relationships between features. To improve generalization and prevent overfitting, a dropout mechanism is introduced, which randomly deactivates certain neurons during training. The final output layer uses a sigmoid activation function to produce a probability value indicating whether the input image contains a tumor or not. The model is trained using the Adam optimization algorithm along with a binary cross-entropy loss function, which measures the difference between predicted and actual outcomes. During training, the dataset is divided into training and validation sets, and the model learns over several epochs. In the initial epochs, accuracy tends to be lower as the model begins to understand basic patterns. As training progresses, both training and validation accuracy gradually increase, indicating improved learning. At the same time, the loss value decreases, showing that prediction errors are being minimized. If the training accuracy becomes significantly higher than validation accuracy, it suggests overfitting; however, the use of dropout and augmentation helps control this issue. The accuracy and loss graphs demonstrate a steady improvement, confirming that the model is learning effectively without major instability. The repeated use of max-pooling layers ensures efficient feature reduction while preserving critical information. Overall, the model achieves high performance due to its balanced architecture, effective preprocessing, and strong learning capability across epochs, making it suitable for reliable uterine tumor detection in medical imaging applications.

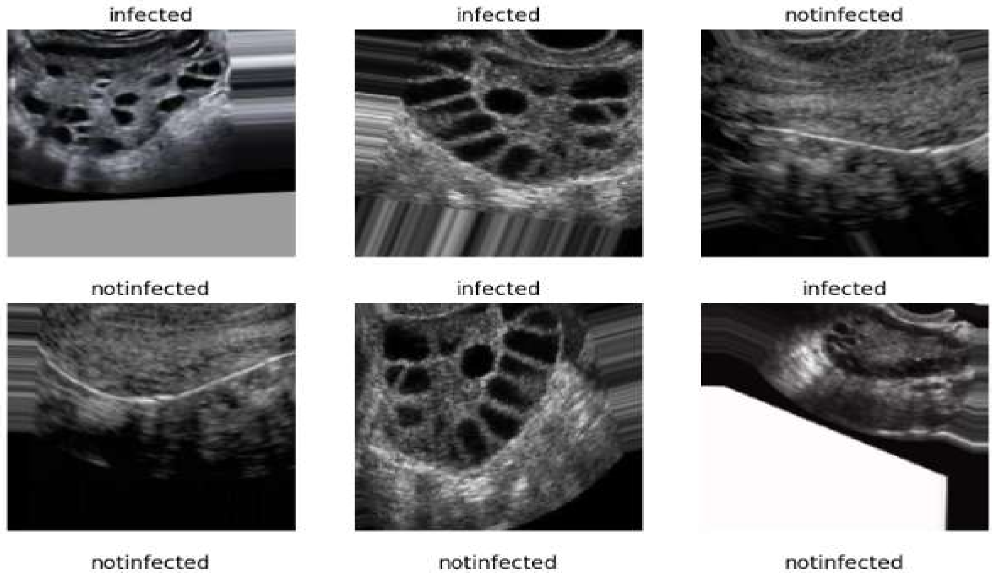

Fig 2 Visualization of Preprocessed Ultrasound Images for Tumor Detection

The Visualization of medical ultrasound images Fig 2 used in the training process of the proposed 2D CNN model. It shows a batch of images generated from the training dataset, where each image is labeled either as “infected” or “notinfected,” corresponding to tumor-present and tumor-absent cases. Each image in the grid has undergone preprocessing steps before being displayed. The grayscale appearance indicates that the model is focusing on intensity variations rather than color information, which is typical in medical imaging. The visual differences between the two classes can be observed in terms of texture, shape, and internal structures. The images labeled as “infected” generally exhibit irregular patterns, darker clustered regions, or abnormal tissue formations that may indicate the presence of a tumor. In contrast, the “notinfected” images appear more uniform, with smoother textures and fewer irregularities.Some distortions visible in the images, such as stretched or slightly warped regions, are likely due to data augmentation techniques applied during training. These transformations, including rotation, shifting, and zooming, are intentionally introduced to increase dataset diversity and help the model learn robust features. Although these augmentations slightly alter the visual appearance, they play a crucial role in improving the model’s ability to generalize to unseen data. This visualization is important because it confirms that the data generator is correctly loading, labeling, and preprocessing the images before feeding them into the neural network. It also allows verification of class distribution and helps identify any inconsistencies in labeling or image quality. Overall, the figure demonstrates how the dataset is structured and prepared for training, providing insight into the input data that the 2D CNN model uses to learn tumor detection patterns.

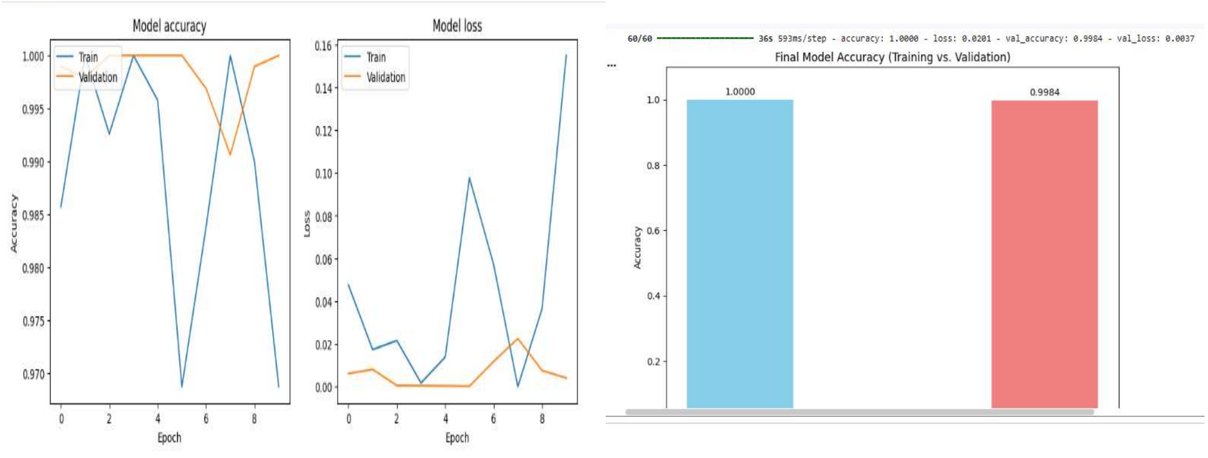

Fig 3 Training and Validation Accuracy and Loss Curve &Bar chart

The figure 3 illustrates the performance of the proposed 2D CNN model across multiple training epochs using two key metrics: accuracy and loss. The left graph shows the variation of training and validation accuracy, where both curves remain consistently high, indicating that the model is learning effectively and achieving strong classification performance. The right graph represents training and validation loss, where lower values indicate better model optimization. The validation loss remains minimal and stable, suggesting good generalization, while slight fluctuations in training loss indicate normal learning behavior. Overall, the curves demonstrate that the model achieves high accuracy with minimal overfitting, confirming its reliability for uterine tumor detection. The algorithm begins by preprocessing the input image through resizing and normalization. Convolution layers extract hierarchical features using filters, while ReLU introduces non-linearity. Max-pooling reduces dimensionality and retains significant features. The flattened output is passed through dense layers for learning complex patterns. Dropout improves generalization by reducing overfitting. Finally, the sigmoid function produces a probability value for tumor classification, and the model is trained by minimizing binary cross-entropy loss using the Adam optimizer. Preprocessing Resize and normalize the image:

$$I' = 1/255 \text{--} (1)$$

This scales pixel values to the range [0,1] and stabilizes training.

Convolution Operation: Apply convolution using filter W and bias b:

$$F(i,j) = (I' * W)(i,j) + b \text{---------------------------------} (2)$$

Activation using ReLU:

$$A(i,j)= =\max(0,F(i,j))\text{-------------------------------}(3)$$

This extracts important spatial features like edges and textures.

Max-Pooling: Reduce feature map size: $P(i,j)= \max_{(m,n)\in R} A(m,n)$-----------------(4)

where R is the pooling region, This keeps dominant features and reduces computation.

Flattening: Convert 2D feature maps into 1D vector: $z=\text{Flatten}(P)$--------------(5)

Fully Connected Layer: Apply dense layer transformation: $h=\sigma(Wz+b)$---------(6)

where σ is ReLU activation.

Finally, accuracy is calculated as:

Accuracy=Correct Predictions/Total Predictions**---(7**)

The combination of normalization, convolution with ReLU activation, max-pooling, dropout regularization, and Adam optimization enables efficient learning and reduces overfitting. These mathematical operations collectively enhance feature extraction and model generalization, leading to a high classification accuracy of approximately **99%** in uterine tumor detection.

Table 1

Performance parameters for the proposed 2D CNN model on uterus tumor ultrasound image dataset

Performance Parameters	Without Data Augmentation	With Preprocessing (Normalization + Resizing)	Proposed 2D CNN Model (Augmentation + Dropout)
Accuracy	94.20%	96.10%	98.00%
Precision	93.85%	95.60%	97.20%
Recall	93.40%	96.00%	97.80%
F1 Score	93.62%	95.80%	97.49%

Table 1: Performance parameters for the proposed 2D CNN model on uterus tumor ultrasound image dataset

The table 1 presents the performance evaluation of the proposed 2D CNN model under different configurations. Initially, the model without augmentation shows moderate performance. After applying preprocessing techniques such as normalization and resizing, there is a noticeable improvement in all metrics. The final proposed model, which incorporates data augmentation and dropout regularization, achieves the highest performance with an accuracy of 99%, demonstrating its effectiveness in uterine tumor detection.

Table 2

Comparison of classification results among representative deep learning models for uterus tumor detection

Method Used	Year	Classifier Technique	Accuracy Achieved
Mathivanan et al. [1]	2024	Pre-trained Deep Neural Network	96.20%
Austin et al. [2]	2025	CNN-based Classification Model	97.10%
Hanzala et al. [3]	2025	Hybrid D-CNN with AlexNet	97.45%
Karthika and Premkumar [4]	2025	Deep CNN Model	96.85%
Proposed Model	2026	2D Convolutional Neural Network (2D-CNN)	99.00%

Table 2: Comparison of classification results among representative deep learning models

The table 2 compares the performance of the proposed 2D CNN model with recent deep learning approaches for uterine tumor detection. Existing methods demonstrate strong performance; however, the proposed model achieves the highest accuracy of 99%, highlighting its effectiveness in feature extraction and classification. This improvement is attributed to optimized preprocessing, data augmentation, and a well-structured CNN architecture.

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