KANVAS: Kolmogorov-Arnold Networks for Visual Analysis in Brain Tumor Stratification

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***Abstract*—Brain tumor classification is a critical task in medical imaging that aids in the early diagnosis and treatment of life-threatening conditions. In this study, we present a novel approach utilizing Kolmogorov-Arnold Networks (KANs) for the classification of brain tumors based on MRI images. The dataset used comprises 7,023 MRI images categorized into four distinct classes: glioma, meningioma, no tumor, and pituitary tumor. Unlike traditional convolutional neural networks (CNNs), which often require extensive computational resources and prolonged training times, KANs leverage mathematical transformations to achieve efficient feature extraction and classification. Our proposed methodology significantly reduces training time while maintaining high classification accuracy, making it a practical alternative to conventional deep learning techniques. Experimental results demonstrate the efficacy of KANs in handling large-scale medical imaging datasets, offering a promising direction for real-world clinical applications.**

***Index Terms*—Kolmogorov-Arnold Networks (KANs), Medical imaging, Tumor diagnosis, Neural networks**

I. Introduction

Brain Tumors are among the most life-threatening medical conditions which can cause severe neurological damage or even death if not identified and treated at the rite time. Some of the main types of brain tumor include meningioma which constituites of about 30 per cent of all brain tumors, glioma and pituitary. Early and accurate identification is vital for effective treatment. However, the traditional manual diagnosis of brain tumors through medical imaging is complex and time consuming, and needs the expertise of radiologists as the changes in the brain tissue casuing the tumor is very subtle.

In recent years, Artificial Intelligence and Machine Learning models, especially deep learning techniques such as Convolutional Neural Networks (CNN), have had a major impact in automating the classification of brain tumors from Magnetic Resonance Imagine (MRI) scans. These models help assist the medical experts by timely identification of brain tumors with great accuracy.

However, traditional deep learning methods often requiring substantially high computational power and extensive training time. At times these limitations cannot be ignored as the medical fraternity demands quick, accurate, efficient and cost-effective methods.

To tackle these challenges, we propose a novel method for classifying brain tumors from MRI images using Kolmogorov-Arnold Networks. KANs are designed to efficiently extract and process images features using mathematical transformations while significantly reducing training time and computational requirements, hence a promising alternative to convolutional deep learning methods in terms of efficiency. In this study we evaluate the performance of various KAN architectures on the MRI images dataset consisting of three types of brain tumors, namely meningioma, glioma and pituitary apart from normal no tumor images as well.The results show the potential of KANs to provide accurate and efficient classification of tumors, showcasing their potential to be used in real-time applications where high performance and computational efficiency are a priority

II. Literature Survey

Kolmogorov-Arnold Networks (KANs) represent a groundbreaking shift in neural network design, inspired by the Kolmogorov-Arnold representation theorem. Unlike traditional neural networks that rely on fixed activation functions at nodes, KANs leverage learnable functions on edges, enabling superior accuracy, interpretability, and efficiency Below, we review key contributions in the field, highlighting the evolution of KAN-based architectures and their potential for advanced image classification and segmentation tasks, particularly in our context of brain tumor detection.

Liu et al.(2024)[1] : This foundational work introduces KANs as alternatives to MLPs, leveraging learnable activation functions on edges instead of fixed node-centric activations. The study demonstrates KANs' superior accuracy, interpretability, and faster scaling laws, particularly in data fitting and PDE solving, establishing a strong theoretical and empirical basis for their adoption.

Dylan Bodner et al.(2024)[2] : This paper integrates KANs' edge-based activation functions into convolutions, creating a novel layer for CNNs. Empirical evaluations on the Fashion-MNIST dataset reveal that CKANs achieve similar accuracy to CNNs with significantly fewer parameters, showcasing their potential for efficient deep learning in vision tasks.

Azam et al.(2024)[3] : This work evaluates KANs' performance in image recognition, highlighting their efficiency on simpler datasets like MNIST. However, the benefits diminish for more complex datasets like CIFAR-10, suggesting limitations in scalability and indicating areas for further optimization in KAN-based architectures.

Li et al.(2024)[4]: By integrating KAN layers into U-Net architectures, this study enhances accuracy and computational efficiency in medical image segmentation.

III. Methodology

A. Data Collection

The dataset used in this research was sourced from Kaggle, an online platform providing access to diverse and high-quality datasets. The selected dataset contains separate folders for training and testing samples, facilitating clear segregation of data for model evaluation. This ensures an unbiased assessment of model performance.

B. Data Transformation

The raw dataset required preprocessing to prepare it for training and testing. A series of transformations were applied to standardize the data format and enhance its compatibility with the model. The transformation steps included:

- **Grayscale Conversion:** Ensures all images are converted to single-channel grayscale.
- **Resizing:** Rescales images to a fixed size of 28×28 pixels to match the model's expected input dimensions.
- **Tensor Conversion:** Converts the image data into tensor format suitable for PyTorch operations.
- **Normalization:** Normalizes pixel values to have a mean of 0.5 and standard deviation of 0.5.

C. Data Loading

The preprocessed data was loaded into PyTorch's DataLoader for efficient batch processing during training and testing. The training dataset was shuffled to ensure diverse batches, while the test dataset remained unshuffled for consistent evaluation. Key configurations for the DataLoader include:

- **Batch Size:** Set to 32 for both training and testing.
- **Shuffling:** Enabled for training to promote generalization and disabled for testing.
- **Parallel Data Loading:** Utilized 4 workers to speed up data loading operations.

D. Model Architectures and Training

Following data preparation, the models were trained using four architectures as proposed by Duylen et al.[2]:

- **KKAN:** A Kolmogorov-KAN variant employing complex learnable functions for feature extraction.
- **KANC:** Combines KANs with additional layers for improved representation learning.
- **KAN:** The foundational Kolmogorov-Arnold Network architecture, utilizing learnable non-linear kernels instead of traditional convolutions.

IV. Architecture

A. KKAN

- **Input Layer:** Accepts the input data, which is preprocessed and formatted to match the expected dimensions of the model.

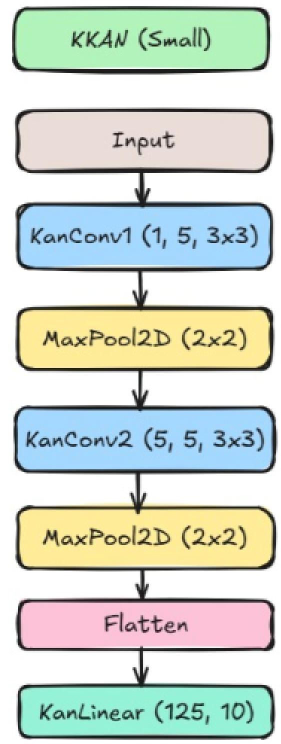

Fig. 1. KKAN (Small)

- **KAN Convolutional Layers:** Includes two sequential KAN convolutional layers. These layers apply Kolmogorov-Arnold Network (KAN)-based convolutional operations, which leverage learnable non-linear functions to extract meaningful features from the input data. Each layer processes the features further, enabling hierarchical representation learning.
- **MaxPooling Layer:** A pooling layer that reduces the spatial dimensions of the feature maps while retaining the most important information. This step helps in reducing computational complexity and prevents overfitting.
- **Flatten Layer:** Converts the multi-dimensional feature maps into a one-dimensional vector, making them suitable for processing by fully connected layers.
- **KAN Linear Layer:** A fully connected layer that maps the extracted features to the output classes using KAN's learnable functions, enabling the model to make predictions.

B. KANC MLP

- **Input Layer:** Processes the input data, ensuring compatibility with the model's expected dimensions.
- **KAN Convolutional Layer 1:** The first KAN convolutional layer applies Kolmogorov-Arnold Network (KAN)-based convolutional operations. It extracts initial features from the input using learnable non-linear kernels.
- **MaxPooling Layer:** Reduces the spatial dimensions of the feature maps generated by the first KAN convo-

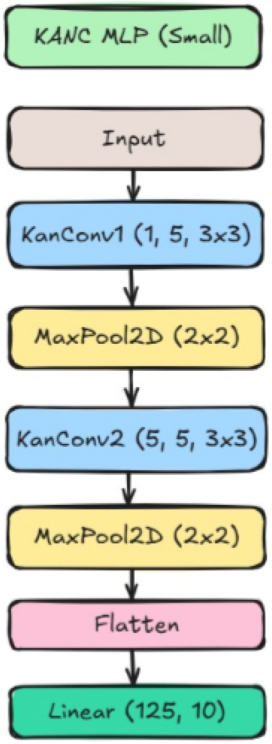

Fig. 2. KANC MLP (Small)

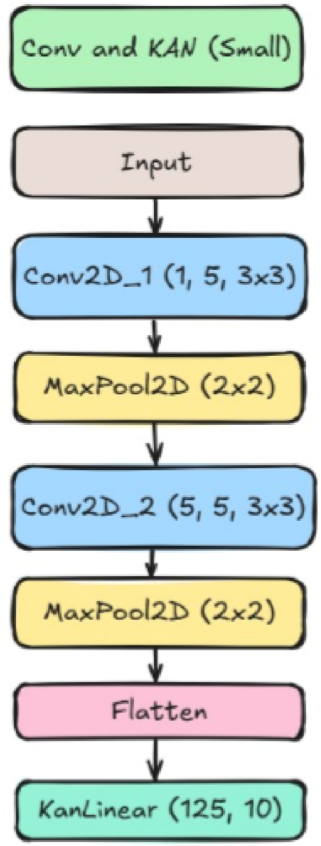

Fig. 3. Conv and KAN (Small)

lutional layer. This operation retains important features while lowering computational complexity.

- **KAN Convolutional Layer 2:** The second KAN convolutional layer further processes the features extracted by the first layer, enabling a deeper representation of the data.
- **MaxPooling Layer:** Another pooling layer that further downsamples the feature maps from the second KAN convolutional layer, reducing the dimensionality while preserving essential information.
- **Flatten Layer:** Converts the multi-dimensional feature maps into a one-dimensional vector, making the data suitable for the fully connected layer.
- **Linear Layer:** A fully connected layer that maps the flattened feature vector to the output classes, producing the final predictions.

C. Conv and KAN

- **Input Layer:** Accepts the input data, which is preprocessed and formatted for compatibility with the model.
- **Convolutional Layer 1 (Conv2D 1):** Applies a standard 2D convolution operation to extract initial features from the input using learnable kernels.
- **MaxPooling Layer:** Reduces the spatial dimensions of the feature maps generated by the first convolutional layer, retaining significant features while minimizing computational load.
- **Convolutional Layer 2 (Conv2D 2):** A second 2D convolutional layer that further processes the extracted features, enabling the model to learn more complex patterns.
- **MaxPooling Layer:** Another pooling layer that downsamples the feature maps from the second convolutional layer, further reducing dimensionality while preserving important information.
- **Flatten Layer:** Transforms the multi-dimensional feature maps into a one-dimensional vector, preparing the data for the final fully connected layer.
- **KAN Linear Layer:** A fully connected layer that utilizes KAN-based learnable functions to map the extracted features to the output classes, producing the final predictions.

V. Results

To evaluate the efficacy of KAN-based architectures in brain tumor classification, we tested different configurations categorized as **Small**, **Medium**, and **Large** architectures. The results demonstrate the performance of each model in terms of classification accuracy:

*a) 1. **Small Architecture**:*

- **KANC MLP**: Achieved an accuracy of **84.82%**, showcasing the baseline performance of edge-based activations in MLP-based setups.

		precision	recall	f1-score	support
glioma	0	0.87	0.82	0.84	300
meningioma	1	0.81	0.82	0.81	306
notumor	2	0.95	0.95	0.95	405
pituitary	3	0.91	0.95	0.93	300
accuracy				0.89	1311
macro avg		0.88	0.88	0.88	1311
weighted avg		0.89	0.89	0.89	1311

Fig. 4. KKAN (Small)

- **KKAN**: Delivered the highest accuracy of **88.94%** among small models, highlighting the strength of incorporating Kolmogorov-Arnold Convolutions.
- **Conv_KAN**: Attained an accuracy of **87.34%**, indicating the robustness of blending KAN-based activations with traditional CNN layers.

*b) 2. **Medium Architecture**:*

- **KANC MLP**: Improved upon its small counterpart with an accuracy of **87.64%**, demonstrating better performance with increased model complexity.
- **KKAN**: Maintained a competitive accuracy of **88.48%**, reflecting consistent scalability in performance.
- **Conv_KAN**: Outperformed other medium architectures with an accuracy of **89.09%**, establishing its effectiveness in leveraging convolutional layers alongside KAN principles.

*c) 3. **Large Architecture**:* **Conv_KAN**: Achieved an accuracy of **84.59%**, suggesting diminishing returns with larger architectures, likely due to overfitting or inefficiencies in parameter utilization.

*d) **Key Observations**:*

- KKAN consistently performs well across small and medium architectures, emphasizing the advantages of Kolmogorov-Arnold-based layers in compact setups.
- Conv_KAN exhibits superior performance in the medium architecture, suggesting an optimal balance of complexity and generalization.
- Larger architectures show reduced accuracy, indicating the importance of architectural efficiency and the potential for overfitting with increasing parameters.

These results underscore the promise of KAN-based approaches in medical image classification, with Conv_KAN emerging as a particularly effective framework for medium-sized configurations. Further optimization and regularization strategies may enhance the performance of larger models.

VI. CONCLUSION

In this study, we demonstrated the potential of Kolmogorov-Arnold Networks (KANs) for brain tumor classification using MRI images. The results of the experiments confirmed the efficient performance of several architectures based on KANs, highlighting the ability to achieve competitive classification accuracy while maintaining computational efficiency. Within the tested architectures, the Conv KAN architecture, consisting

		precision	recall	f1-score	support
glioma	0	0.86	0.76	0.80	300
meningioma	1	0.78	0.80	0.79	306
notumor	2	0.89	0.99	0.94	405
pituitary	3	0.96	0.91	0.94	300
accuracy				0.87	1311
macro avg		0.87	0.86	0.87	1311
weighted avg		0.87	0.87	0.87	1311

Fig. 5. Conv KAN (Small)

		precision	recall	f1-score	support
glioma	0	0.79	0.92	0.85	300
meningioma	1	0.89	0.64	0.75	306
notumor	2	0.92	0.99	0.95	405
pituitary	3	0.95	0.96	0.95	300
accuracy				0.88	1311
macro avg		0.89	0.88	0.87	1311
weighted avg		0.89	0.88	0.88	1311

Fig. 6. KKAN (Medium)

		precision	recall	f1-score	support
glioma	0	0.80	0.90	0.85	300
meningioma	1	0.87	0.69	0.77	306
notumor	2	0.94	0.94	0.94	405
pituitary	3	0.88	0.96	0.92	300
accuracy				0.88	1311
macro avg		0.87	0.87	0.87	1311
weighted avg		0.88	0.88	0.87	1311

Fig. 7. KANC MLP (Medium)

		precision	recall	f1-score	support
glioma	0	0.82	0.91	0.86	300
meningioma	1	0.86	0.72	0.79	306
notumor	2	0.91	0.98	0.94	405
pituitary	3	0.96	0.93	0.95	300
accuracy				0.89	1311
macro avg		0.89	0.88	0.88	1311
weighted avg		0.89	0.89	0.89	1311

Fig. 8. Conv KAN (Medium)

		precision	recall	f1-score	support
glioma	0	0.91	0.71	0.80	300
meningioma	1	0.68	0.85	0.75	306
notumor	2	0.94	0.86	0.90	405
pituitary	3	0.89	0.96	0.92	300
accuracy				0.85	1311
macro avg		0.85	0.84	0.84	1311
weighted avg		0.86	0.85	0.85	1311

Fig. 9. KANC MLP (Large)

Architecture	Accuracy
KANC MLP (Small)	84.82%
KKAN (Small)	88.94%
Conv KAN (Small)	87.34%
KKAN (Medium)	88.48%
KANC MLP (Medium)	87.64%
Conv KAN (Medium)	89.09%
KANC MLP (Large)	84.59%

TABLE I
ACCURACY

of a KAN linear layer, for medium sized layouts turned out to be the best performing architecture, as it provided the best trade-off between effective capacity and generalization. These findings emphasize the promising ability of KANs to serve as a practical alternative to traditional deep learning models such as CNNs, particularly in scenarios where computational resources are limited or rapid inference is required. The reduced training times of KANs, along with their competitive accuracy, make them a considerable option for deployment in clinical settings where timely and accurate diagnosis is crucial. The results also tend to prove the assumption that mathematical transformations, which is the main part of KANs may be useful to extract important and complex information from the dataset. This opens up new opportunities for their use beyond the scope of brain tumor classification.

VII. FUTURE WORK

While our work shows promising results, there is always a huge room for improvement. Some of the areas for future work include improving regularization and optimization techniques to improve accuracy. Hybrid or Multimodal Architectures could be looked at by refining and expanding the architectures or by combining KANs with transformers. Focusing on the explainability and interpretability through visualisations or other methods would further help the medical fraternity to make confident decsions as it would give a clearer insight as to why the model is arrives at its prediction.

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