Wildfire Prediction using Convolutional Kolmogorov-Arnold Network

Abstract—**The growing threat of wildfires is considered an important large-scale environmental challenge, and their fast and correct detection have an essential role in lessening the devastating effects of such events. Some effective tools are provided by advances in machine learning, especially Convolutional Neural Networks (CNNs), for wildfire detection from satellite imagery which has high computational cost that forbids real-time application. We propose a hybrid model combining an architecture based on Kolmogorov-Arnold Networks (KAN) with CNN. By using learnable nonlinear activation functions, KAN can make more effective use of the parameters compared to traditional multi-layer perceptrons, with less computational overhead and without loss of accuracy. The model integrates the spatial feature extraction capability of CNNs with the parameter efficiency of KAN, hence achieving superior performance in detecting wildfires from satellite images. With these, the experimental results indicate that the proposed KAN-CNN hybrid outperforms the state-of-the-art CNN-based architecture with a large margin, with a test accuracy of 97.32% using fewer parameters and faster convergence. It is thus suitable for large-scale and real-time wildfire monitoring and detection systems, with possible applications in broader environmental monitoring tasks.**

Index Terms—**kolmogorov-arnold network, learnable nonlinear activation, convolutional neural network.**

I. Introduction

The issue of wildfires has evolved into a serious environmental challenge, becoming one of the leading causes of severe ecological degradation and a significant threat to human lives. Effective mitigation of losses caused by these fires necessitates immediate detection and response. Advances in satellite imagery have enabled the development of various techniques for wildfire detection, among which machine learning stands out as a powerful approach. Notably, Convolutional Neural Networks (CNNs) have proven effective in image classification and pattern recognition tasks due to their hierarchical feature extraction capabilities [1]. CNNs are particularly well-suited for capturing spatial features in satellite images, making them ideal for wildfire detection. However, despite their performance, CNNs often require a large number of parameters, resulting in higher computational costs and slower inference times, which can be a significant drawback in real-time monitoring applications.

While satellite imagery has significantly improved wildfire detection methods, current models, including CNNs, frequently suffer from reduced accuracy due to their complexity, which leads to increased computational demands and slower inference times. The Kolmogorov-Arnold Networks (KAN) based CNN model addresses these challenges by leveraging the strengths of KANs, which utilize learnable nonlinear functions to enhance both accuracy and computational efficiency. This hybrid approach capitalizes on the parameter efficiency of KANs, optimizing the detection process and improving the speed and accuracy of wildfire predictions from satellite data.

In contrast to traditional multilayer perceptrons that rely on fixed nonlinear activation functions, KANs introduce an innovative architecture that employs learnable nonlinear activation functions [2]. They operate based on the Kolmogorov-Arnold Representation theorem, allowing them to approximate complex functions with fewer parameters, thereby increasing computational efficiency. KAN architectures have demonstrated significant success across various domains, including their application with wavelet functions [3]. The KAN-CNN hybrid model combines the spatial feature extraction capabilities of CNNs with the parameter efficiency of KANs, ensuring greater accuracy in wildfire detection from satellite images without sacrificing computational efficiency. Furthermore, CNNs have been effectively applied to satellite data for predicting forest fires, showcasing the potential of deep learning in identifying fire-prone patterns [4]. This success has influenced the KAN-CNN model, emphasizing the importance of integrating CNNs for spatial feature extraction with knowledge-aware components to enhance predictive performance further. Additionally, Atrous Spatial Pyramid Pooling has introduced greater interpretability into CNN-based models for wildfire prediction [5]. With the incorporation of appropriate agnostic attention mechanisms, the KAN-CNN model can significantly enhance early detection systems, enabling more rapid and reliable responses in wildfire management.

The contributions of this paper are summarized as follows:

- **Novel Architecture of KAN-CNN:** A hybrid architecture by combining KAN with CNN for a novel approach toward detecting wildfires from satellite images but with fewer parameters.
- **Efficient Non-Linear Approximation:** The KAN layers make use of the Kolmogorov-Arnold representation theorem to achieve improved representability for complex nonlinear patterns with many fewer trainable parameters compared to classic techniques.
- **Parameter Optimization with Grid Size and Spline Order:** We fine tune the grid size and spline order in the KAN Linear layer to provide more precise control over the granularity and flexibility of feature representation, hence minimizing overfitting and increasing generalization.
- **Reduced Computational Complexity:** The proposed model achieves competitive performance with significantly fewer parameters, making it suitable for real-time

applications with limited computational resources.

II. Related Works

Recent advances in machine learning have yielded great results in wildfire detection using satellite images, and several models and techniques is proposed with improved accuracy and interpretability. Kolmogorov-Arnold Networks (KANs) is an alternative to traditional Multi-Layer Perceptrons (MLP), in which their learnable activation functions provided improved accuracy for complex tasks [2]. By incorporating the functions of wavelets into KANs, an Wav-KAN architecture has been developed which is efficient for capturing both high and low frequency data components [3]. Thus, improving their performance and interpretability. In time series forecasting, KANs have been applied which demonstrated superior performance and parameter efficiency over traditional MLPs, particularly in satellite traffic forecasting, which may also apply to wildfire prediction [6].

Building on KAN's temporal data capabilities, Temporal KANs (TKANs) is proposed which fused KAN and Long short term Memory (LSTM) architectures to achieve better multi-step time series forecasting [7]. This is a method potentially useful for predicting wildfire spread. In the realm of computer vision tasks, KANs remain competitive with benchmark vision datasets through the KAN-Mixer architecture, showcasing their potential in satellite-based wildfire detection [8]. Moreover KAN is extended into graph-structured data (GKANs), which achieved better accuracy in semi-supervised learning tasks, offering potential for developing wildfire models using geographic data [9].

Additionally, the application of convolutional autoencoders outperformed logistic regression and random forest models to predict day-ahead wildfire spread from satellite data [10]. Machine learning techniques such as Random Forest, Boosted Regression Trees, and Support Vector Machines are used to model human-caused wildfire predictions, outperforming logistic regression models and emphasizing the need for robust predictive tasks in wildfire-related research [11].

Combined statistical and machine learning methods is deployed to forecast extreme wildfire frequencies and sizes within a high-dimensional, zero-inflated dataset while Random Forest is used to enhance predictive accuracy [12]. Deep learning has made recent strides in wildfire prediction. Incorporated spatio-temporal satellite and sensor data, as well all-convolutional network (AllConvNet) for wildfire burn prediction, demonstrating superior accuracy compared to traditional models such as SegNet and logistic regression [13]- [14].

Researchers also noted the achievements and challenges in applying deep learning models to wildfire detection, mapping, and prediction using satellite remote sensing data [15]. Besides, researchers developed an interpretable CNN model with Atrous Spatial Pyramid Pooling (ASPP) for predicting forest fire spread, achieving an F1-score of 97% [5]. The model further enhanced with interpretability using Grad-CAM algorithm for feature extraction.

Recent achievements by machine learning, especially with the enhancement of KANs and their variants such as Wav-KAN, TKAN, and GKAN, have succeeded in enhancing the performance and interpretability of wildfire predictions concerning both time series and computer vision tasks. Besides, other deep learning-based models like convolutional autoencoders, AllConvNet, and interpretable CNNs outperformed other traditional approaches in wildfire prediction and mapping using satellite data. These attest to an increase in capability for machine learning to predict and understand the behavior of wildfires.

III. Methodology

This section covers the processes and approaches taken to construct the wildfire prediction model. The methodology includes numerous phases, from dataset preparation and preprocessing to the implementation of the suggested hybrid Kolmogorov-Arnold Network (KAN) and Convolutional Neural Network (CNN) architecture. The goal is to use the strengths of both KAN and CNN to produce efficient and reliable wildfire identification using satellite photos. We detail the dataset used, the architecture of the proposed model, and the methods performed during training, validation, and testing.

A. Dataset Description

The dataset for this study is sourced from the Forest Fires - Open Government Portal [16]. The dataset contains satellite images with dimensions of 350×350 pixels, divided into two categories: 22,710 images labeled as "Wildfire" and 20,140 images labeled as "No Wildfire".

Images are split into three sets to support the training, testing, and validation of machine learning models. 70% of the dataset is used for training the model, 15% is set aside for testing to evaluate the model's performance on unseen data, and the remaining 15% is used for validation to fine-tune the model. Fig. 1 displays the sample of both classes "Wildfire" and "No Wildfire".

Fig. 1. Sample satellite images from the dataset. (a) Images labeled as "Wildfire". (b) Images labeled as "No Wildfire".

B. Proposed KAN-CNN Model

The proposed model of the KAN-CNN reaps the advantages of the strengths provided by both the Kolmogorov Arnold Network (KAN) and Convolutional Neural Networks (CNN). First, KAN provides the compact model with fewer parameters compared to traditional multilayer perceptrons (MLPs), hence suitable for efficient computation. Unlike in MLPs using fixed and predefined activations like ReLU or Sigmoid, KAN introduces nonlinear, learnable activations which allow it to dynamically adjust and optimize during training. This characteristic provides greater flexibility and adaptability in learning complex data patterns.

KANs are based on the Kolmogorov-Arnold representation theorem, which postulates that any multivariate continuous function can be represented as a finite composition of continuous univariate functions. KAN can decompose complex multivariate mappings to simpler, tractable functions, ensuring computational efficiency and minimal risk of overfitting for the model. Convolutional layers in the proposed KAN-CNN model extract spatial features from input data. These extracted features are then fed into the KAN layers, where the learnable nonlinear activations perform the function approximation. The model combines CNN's feature extraction with KAN's efficient function representation. Thus, the model is likely to achieve higher accuracy and faster convergence with fewer parameters, making it ideal for applications where precision and computational efficiency must go hand in hand.

$$f(\mathbf{x}) = f(x_1, \cdots, x_n) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^{n} \varphi_{q,p}(x_p) \right) \tag{1}$$

$$\mathrm{KAN}(\mathbf{x}) = (\Phi_{L-1} \circ \Phi_{L-2} \circ \cdots \circ \Phi_1 \circ \Phi_0)\, \mathbf{x}. \tag{2}$$

Equation 1 represents a multivariate continuous function being approximated by KAN based on the Kolmogorov-Arnold theorem. The summation over q from 1 to $2n+1$ represents the decomposition into univariate functions Φ_q, while each inner sum computes a function $\phi_{q,p}(x_p)$ over individual inputs x_p. Here, Φ_q and $\phi_{q,p}$ are continuous functions learned during training, which allow the model to approximate the original multivariate function effectively. The overall KAN network is defined by composing these functions as shown in Equation 2 denotes the layers of learned univariate functions, and x represents the input data being processed through the network.

This decomposition allows KAN to handle complex, nonlinear transformations with fewer parameters, improving computational efficiency and reducing the risk of overfitting, especially when working with high-dimensional data.

Fig. 2 presents the detailed architecture of the proposed KAN-CNN model. Table I shows the number of parameters and output shapes for each layer of the model. The model initializes with a series of combinations of Conv2d, BatchNorm2d and MaxPool2d layers. MaxPool2d progressively reduces spatial dimensions. The output of the convolutional layer is then flattened before passing it to the KANLinear layers that maps the features to progressively smaller features spaces finally to a output neuron.

TABLE I
LAYER DETAILS WITH OUTPUT SHAPE AND PARAMETERS

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 4, 320, 320]	112
BatchNorm2d-2	[-1, 4, 320, 320]	8
MaxPool2d-3	[-1, 4, 160, 160]	0
Conv2d-4	[-1, 8, 160, 160]	296
BatchNorm2d-5	[-1, 8, 160, 160]	16
MaxPool2d-6	[-1, 8, 80, 80]	0
Conv2d-7	[-1, 16, 80, 80]	1,168
BatchNorm2d-8	[-1, 16, 80, 80]	32
MaxPool2d-9	[-1, 16, 40, 40]	0
Conv2d-10	[-1, 32, 40, 40]	4,640
BatchNorm2d-11	[-1, 32, 40, 40]	64
MaxPool2d-12	[-1, 32, 20, 20]	0
SiLU-13	[-1, 12800]	0
KANLinear-14	[-1, 64]	0
SiLU-15	[-1, 64]	0
KANLinear-16	[-1, 128]	0
SiLU-17	[-1, 128]	0
KANLinear-18	[-1, 2]	0
Total params		6,336
Trainable params		6,336
Non-trainable params		0

The grid size and spline order of the KANLinear layer play a significant role in the model's capacity to learn complex, non-linear patterns with fewer parameters. This approach introduces an adaptive mechanism where the grid size determines the granularity of the spatial features, while the spline order controls the smoothness and flexibility of the function approximation. By tuning these hyperparameters, the model can capture intricate details in the data while maintaining computational efficiency.

Grid size and spline order is set to seven and five respectively. A total of 6,336 parameters are trained compared to millions of parameters in traditional CNN and other MLP architectures. AdamW optimizer is utilized to train the KAN-CNN with learning rate 0.0001 and weight decay 0.0001. The training data is normalized before feeding it to the model. The batch size set to 256 and model training is set to 20 epochs.

This is particularly crucial for wildfire detection, as it enables the model to generalize well across diverse environmental conditions, ensuring accurate predictions with minimal overfitting. The novelty of this paper lies in leveraging this combination of grid size and spline order in the KANLinear layer, which leads to a significant reduction in the number of trainable parameters compared to traditional CNN architectures, without sacrificing accuracy.

IV. RESULTS AND ANALYSIS

In this section, we present the results of our proposed KAN-CNN model for wildfire detection. Following this, we provide a comparison of the KAN-CNN model's performance with other deep learning architectures, including a custom CNN, Multi-Head Attention-based CNN, and ResNet50. The performance of each model is analyzed based on accuracy, F1-score, precision, recall, and the confusion matrix.

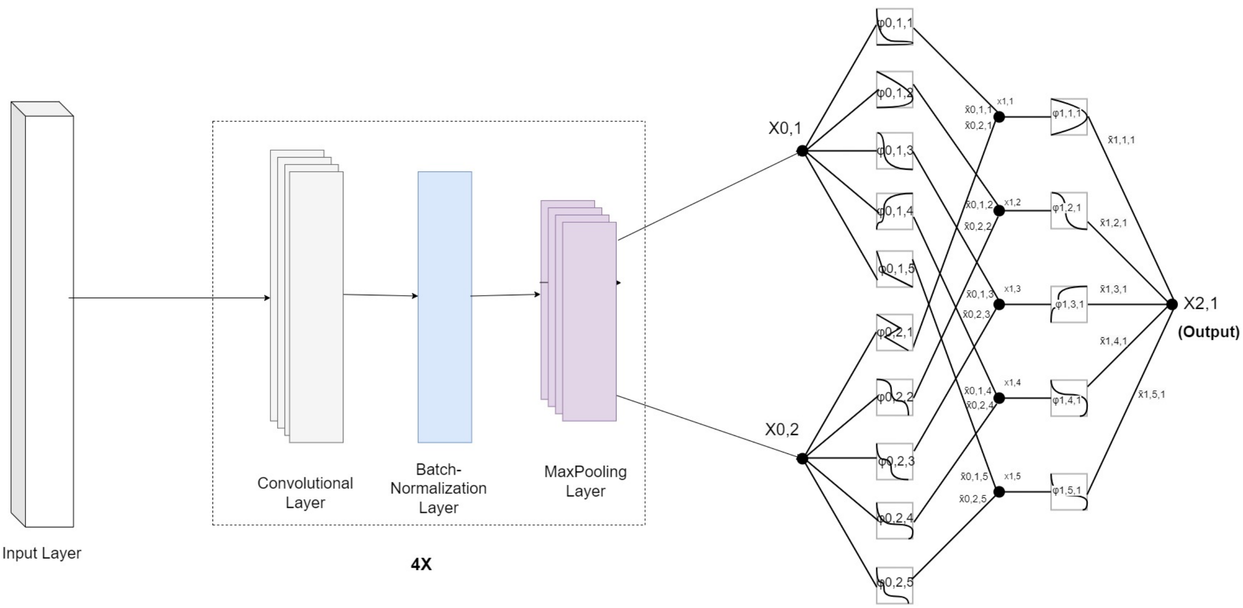

Fig. 2. Model Architecture of proposed KAN-CNN model.

A. Proposed KAN-CNN

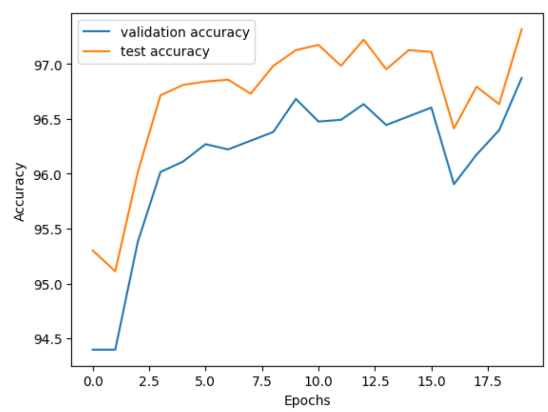

Fig. 3. Accuracy curve of the KAN-CNN model.

The KAN model is specifically designed for this task with its novel learnable activation functions, leading to better performance in capturing both simple and complex patterns in wildfire images. KAN achieved a test accuracy of 97.32%. The model closely reaches or outperforms all other approaches in both accuracy and computational efficiency, using fewer parameters. The KAN's ability to generalize well can be attributed to its adaptability in learning complex non-linear relationships. Fig. 3 shows the validation and test accuracy curve of the KAN-CNN model over training time.

Fig. 4 shows the ROC curve for the proposed KAN-CNN model, demonstrating an area under the curve (AUC) value of 1.00, indicating excellent performance. This high AUC value suggests that the model performs well in distinguishing between the two classes: "Wildfire" and "No Wildfire," based on the satellite imagery data.

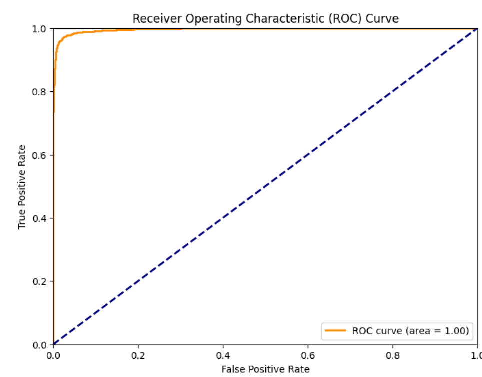

Fig. 4. ROC curve of the KAN-CNN model.

Fig. 5 depicts the confusion matrix of the KAN-CNN model, which demonstrates that the model achieved by correctly classifying 97.3% of positive and negative labels. It is identifying a high number of correct predictions (2,753 true negatives and 3,378 true positives), alongside 67 false positives and 102 false negatives, indicating a relatively small margin of error. This matrix provides a snapshot of the model's ability to handle binary classification tasks effectively.

B. Custom CNN

To compare with the proposed model we have developed a custom CNN. It consists of three convolutional blocks, each with 2D convolutional layers, batch normalization, SeLU activation, and max pooling to reduce spatial dimensions. The input image size is 224×224×3. The first block uses 48 filters,

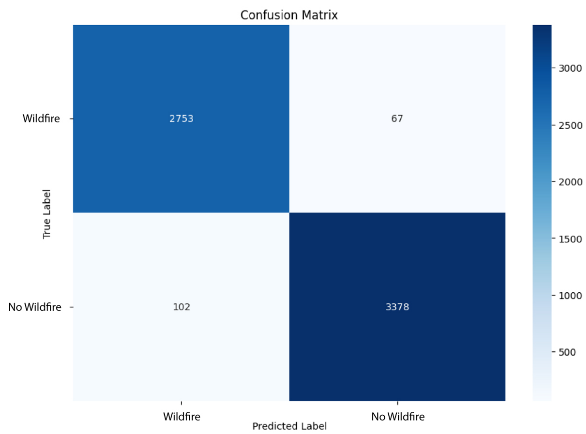

Fig. 5. Confusion matrix of the KAN-CNN model.

followed by 96 and 128 filters in the second and third blocks, respectively. After flattening the output from the convolutional layers, a fully connected layer with 448 units and a dropout rate of 0.3 is applied to prevent overfitting. The final layer uses a softmax activation function to classify the image into wildfire or no wildfire.

The model is compiled with categorical cross-entropy loss and the Adam optimizer. While the model achieved 97.46% accuracy on the test set. Despite this, the custom CNN provides a solid baseline for wildfire detection. Fig. 6 displays the training and validation accuracy and loss curves, where no significant overfitting behavior is observed.

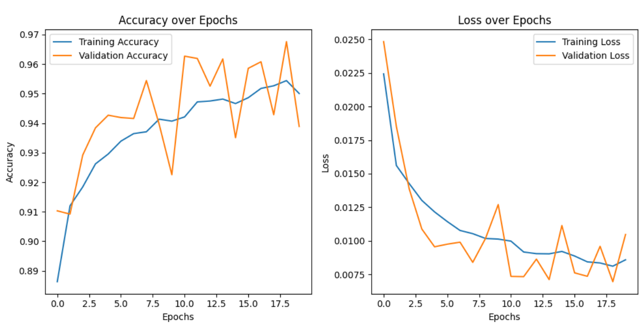

Fig. 6. Accuracy and loss curve of custom CNN model.

C. Multi-Head Attention-based CNN

The Multi-Head Attention-based CNN follows the similar structure to the custom CNN in terms of the convolutional blocks and overall layer design, including the use of 2D convolutional layers, batch normalization, SeLU activation, and max pooling. Like the previous model, it also includes a fully connected layer with 448 units and a dropout rate of 0.3 to prevent overfitting, along with a softmax output layer for classification. This model differs in the introduction of a multi-head attention mechanism. After the final convolutional block, the output is reshaped to fit a multi-head attention layer with four heads and a key dimension of 128 is utilized. This layer allows the model to focus on different parts of the image simultaneously, improving its ability to capture global dependencies. The output of the attention layer is then passed through a global average pooling layer before the fully connected layers. The model achieved 89% accuracy on the test set. Accuracy and loss curves are displayed in Fig. 7.

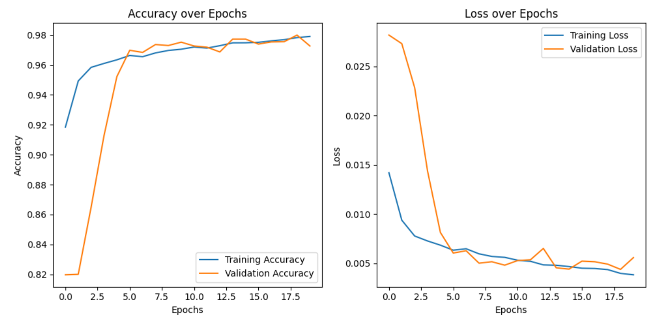

Fig. 7. Accuracy and loss curve of Multi-Head Attention-based CNN model.

D. ResNet50

The ResNet50-based model utilized for this task is built upon the ResNet50 architecture, pre-trained on ImageNet data. The ResNet50 model, known for its deep layers and residual connections. The ResNet50 model leverages pre-trained weights, allowing it to take advantage of previously learned features. The pre-trained model is loaded without the top classification layers, and the convolutional layers are frozen to prevent them from being updated during training. After the ResNet50 base, a Global Average Pooling layer is added to reduce the dimensionality of the output from the convolutional blocks. Following that, a fully connected layer with 128 units and ReLU activation is applied, similar to the fully connected layers in the previous models. A dropout rate of 0.5 is introduced to prevent overfitting. Finally, the model uses a sigmoid activation in the output layer for binary classification, differentiating between wildfire and no-wildfire images. This model achieved 91% accuracy on the test set. Like the previous models, the training and validation curves Fig. 8 indicate stable training with no significant overfitting.

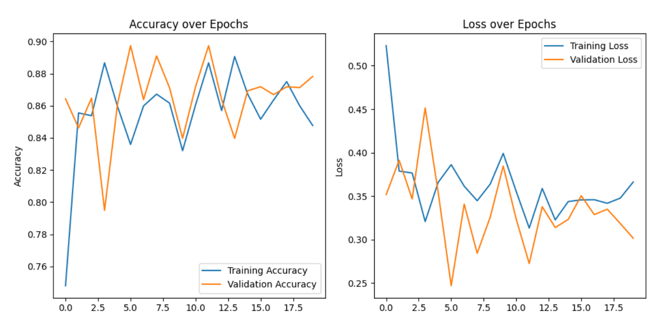

Fig. 8. Accuracy and loss curve of ResNet50 model.

To evaluate the performance of the models, we compare the validation and test accuracy across different models over 20 epochs. Table II shows the accuracy trends of the custom CNN, ResNet50, Multi-Head Attention-based CNN, and KAN-CNN models.

TABLE II
EPOCH-WISE ACCURACY COMPARISON OF DIFFERENT MODELS

Epoch	**Custom CNN (Val)**	**ResNet50 (Val)**	**Multi-Head Attention CNN (Val)**	**KAN-CNN (Val)**
0	89%	76%	84%	96%
5	93%	87%	96%	97%
10	94%	88%	97%	97%
15	96%	89%	97%	97%
20	96%	89%	97%	97%

The KAN-CNN model consistently outperformed the other models across all epochs, maintaining a near-stable accuracy of 97% after just a few epochs. In contrast, the ResNet50 model started with lower accuracy but gradually improved to around 0.89 by epoch 20. The Multi-Head Attention-based CNN and the custom CNN models also showed steady improvement, with the former reaching the highest accuracy of 97%.

To comprehensively evaluate the performance of the different models, several metrics are considered, including accuracy, precision, recall, and F1-score. Table III shows the performance comparison between the custom CNN, Multi-Head Attention-based CNN, ResNet50, and the proposed KAN-CNN model. The Multi-Head Attention-based CNN achieved the highest accuracy of 98.01%, followed closely by the custom CNN and KAN-CNN models, both demonstrating strong performance across all metrics. In contrast, the ResNet50 model displayed significantly lower performance, with an accuracy of 88.53% and lower precision, recall, and F1-scores.

TABLE III
PERFORMANCE COMPARISON OF MODELS

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
Custom CNN	97.46	97.46	97.46	97.46
Multi-Head Attention CNN	98.01	98.04	98.01	98.01
ResNet50	88.53	88.53	88.53	88.52
KAN-CNN	**97.32**	**97.32**	**97.32**	**97.32**

V. CONCLUSTION

In this study, we proposed a hybrid KAN-CNN model for wildfire detection using satellite imagery. The proposed model leverages the strengths of a CNN in spatial features extraction and the efficiency of KAN in its parameters. Our KAN-CNN model has outperformed to other traditional architectures such as customer CNNs, Multi-Head Attention-based CNNs, and ResNet50. It achieved a test accuracy of 97.32% compared with the results shown by other models in accuracy and computational efficiency. The major advantages of the KAN-CNN model: high accuracy with significantly fewer parameters, making it lightweight. Furthermore, the architecture of KAN allowed this model to converge faster; that is, it required fewer epochs to learn from complex patterns present in the wildfire image datasets compared to traditional deep learning models. This is more effective compared to other models, such as ResNet50 which requires more computations and takes longer to train.

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