# A COMPREHENSIVE SURVEY ON KOLMOGOROV ARNOLD NETWORKS (KAN)

#### Tianrui Ji

Department of Applied Mathematics Xi'an Jiaotong-Liverpool University Tianrui.Ji23@student.xjtlu.edu.cn

#### **Yuntian Hou**

Department of AI and Advanced Computing Xi'an Jiaotong-Liverpool University Yuntian. Hou20@student.xjtlu.edu.cn

#### Di Zhang

Department of AI and Advanced Computing Xi'an Jiaotong-Liverpool University Di.Zhang@xjtlu.edu.cn

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# **ABSTRACT**

Through this comprehensive survey of Kolmogorov-Arnold Networks (KAN), we have gained a thorough understanding of its theoretical foundation, architectural design, application scenarios, and current research progress. KAN, with its unique architecture and flexible activation functions, excels in handling complex data patterns and nonlinear relationships, demonstrating wide-ranging application potential. While challenges remain, KAN is poised to pave the way for innovative solutions in various fields, potentially revolutionizing how we approach complex computational problems.

# 1 Introduction

# 1.1 Research Background

Kolmogorov-Arnold Networks (KAN) are an emerging neural network architecture based on the theorems of Kolmogorov and Arnold. These theorems demonstrate that any continuous multivariable function can be represented as a superposition of a finite number of univariate functions. This discovery provides a solid mathematical foundation for the design of KAN, allowing it to replace the fixed linear weights in traditional neural networks with learnable univariate functions, thereby enhancing the model's flexibility and interpretability.

Kolmogorov's theorem, proposed in 1957, states that any continuous multivariable function can be represented as a finite superposition of univariate functions. This research laid the theoretical groundwork for the development of KAN, enabling it to be applied to more complex function representation and learning tasks [1]. The application of KAN is supported by several classical works in numerical analysis and partial differential equation (PDE) solving. For instance, Babuska and Rheinboldt [2] discussed the application of adaptive finite element methods in solving PDEs, providing theoretical background for the application of KAN in numerical analysis. The CFL condition, introduced by Courant, Friedrichs, and Lewy [3], is crucial in numerical analysis and also supports the understanding of KAN in PDE solving. Additionally, the regularization method proposed by Tikhonov [4] plays a key role in dealing with ill-posed problems and PDE solving, significantly influencing the application of KAN in data fitting techniques [2, 3, 4].

In recent years, the application of KAN in machine learning has attracted widespread attention. Its main advantages lie in the flexibility and interpretability of the model. Unlike traditional multilayer perceptrons (MLP), KAN does not have fixed activation functions but uses learnable univariate functions. This characteristic allows KAN to excel in data fitting and complex function learning tasks. For example, Liu et al. [5] demonstrated the superior performance of KAN in data fitting and PDE solving, showing that even smaller KAN models can achieve or surpass the performance of MLPs in these tasks [5].

Another significant advantage of KAN is its performance in handling high-dimensional data. Xu et al. [6] applied KAN in time series analysis, demonstrating KAN's capability in capturing complex temporal dependencies. Furthermore, the application of KAN in graph-structured data processing and hyperspectral image classification also showcases its broad applicability and excellent performance [7].

# 1.2 Research Objectives

This paper aims to systematically review the theoretical foundation, implementation methods, and performance of KAN in various applications. The specific objectives include:

- 1. To elucidate the basic structure and working principles of KAN.
- 2. To explore the implementation methods and challenges of KAN in different tasks.
- 3. To analyze the performance of KAN in practical applications and compare it with other models.
- 4. To summarize the current research progress and propose future research directions.

Through this review, readers will gain a comprehensive understanding of the current state of KAN research and its development potential, providing valuable references for subsequent research and applications.

# 2 Kolmogorov-Arnold Representation Theorem Overview

# 2.1 Historical Background and Proponents

The Kolmogorov-Arnold theorem was proposed by the renowned Russian mathematician Andrey Kolmogorov in 1957, addressing the representation problem of continuous multivariable functions. Kolmogorov's work is considered a milestone in the field of mathematics as it provided a revolutionary method to decompose complex multivariable functions into simple univariate functions. This theoretical breakthrough had a profound impact on approximation theory and laid the groundwork for subsequent research.

Andrey Kolmogorov was one of the most influential mathematicians of the 20th century, making significant contributions to various fields including probability theory, topology, mechanics, and function approximation. In 1957, Kolmogorov published his research on the representation of continuous multivariable functions, proposing that any continuous multivariable function can be represented as a superposition of a finite number of continuous univariate functions [1]. This discovery greatly advanced the fields of function approximation and numerical analysis.

Following Kolmogorov's theoretical proposal, another prominent Russian mathematician, Vladimir Arnold, further extended Kolmogorov's work in 1958. Arnold's research validated the universality of Kolmogorov's theorem and demonstrated its effectiveness in representing higher-dimensional functions. He proved that even complex high-dimensional functions can be approximated by a finite number of simple univariate functions [8]. Arnold's work not only reinforced the foundation of Kolmogorov's theory but also directed further research in this area.

The research contributions of Kolmogorov and Arnold are significant not only in theoretical terms but also in practical applications. By decomposing complex multivariable functions into simple univariate functions, the Kolmogorov-Arnold theorem provides powerful tools and methods for fields such as machine learning, data fitting, and partial differential equation (PDE) solving. The proposal and validation of this theorem mark an important milestone in mathematical analysis and applied mathematics.

#### 2.2 Core Content and Mathematical Expression of the Theorem

Kolmogorov's theorem states that any continuous multivariable function can be represented as a superposition of a finite number of continuous univariate functions. Specifically, for an n-dimensional continuous function  $f(x_1, x_2, \ldots, x_n)$ , there exists a set of continuous univariate functions  $g_i$  and  $h_{ij}$  such that:

$$f(x_1, x_2, \dots, x_n) = \sum_{i=1}^{2n+1} g_i \left( \sum_{j=1}^n h_{ij}(x_j) \right)$$

This theorem indicates that complex multivariable functions can be represented through combinations of simple univariate functions, providing new perspectives for neural network design [1]. This form of representation addresses part of the challenge posed by Hilbert's thirteenth problem regarding the decomposition of multivariable functions, highlighting the feasibility of function decomposition [8, 9].

In the implementation of Kolmogorov-Arnold Networks (KAN), B-splines (basic spline functions) are used for function approximation. B-splines are constructed based on basic spline functions by selecting appropriate knots and applying the Cox-de Boor recursion formula. This approximation method can effectively represent the local characteristics of complex functions in multiple dimensions while maintaining overall mathematical rigor. KAN utilizes this approach to more accurately model and predict multidimensional data, demonstrating the practical application value of the Kolmogorov-Arnold theorem in modern data science and neural network design.

# 2.3 Applications in Function Approximation and Multivariable Function Decomposition

Despite the theoretical power of the Kolmogorov-Arnold theorem, there are some limitations in practical applications. For instance, highly discontinuous functions and those with complex topological structures may encounter difficulties when represented using this theorem. Compared to multilayer perceptrons (MLPs), Kolmogorov-Arnold Networks (KAN) theoretically possess greater expressive power, as they can represent arbitrary multivariable functions. However, in practice, KANs have higher computational complexity, especially when a large number of function superpositions are required, making them less efficient than MLPs [10, 11].

Attempts to apply the Kolmogorov-Arnold theorem to neural networks began in the late 20th century. However, due to limited computational capacity and algorithm optimization technologies at the time, these attempts did not achieve significant success. Specifically, the computational resources available then could not effectively handle the large number of function superpositions and complex nonlinear relationships, limiting the practical application of KANs [12, 13].

In recent years, the Kolmogorov-Arnold theorem has regained attention due to the work of Liu et al. They improved the performance of neural networks in handling complex data relationships by introducing learnable univariate functions [5]. Additionally, new research efforts have rapidly emerged in this field, such as Wavelet-KAN (Wav-KAN) and the quantum version of KAN (VQKAN), further expanding the application scope and performance of KANs [10, 9]. Therefore, it is necessary to recompile the related work on KAN networks, providing a comprehensive reference for researchers in this field. This will not only help understand the existing research outcomes but also offer valuable guidance for future research directions.

# 3 Advantages and Performance of KAN Networks

#### 3.1 Performance Comparison with Traditional Multilayer Perceptrons (MLPs)

Kolmogorov-Arnold Networks (KAN) exhibit significant advantages over traditional neural networks such as Multilayer Perceptrons (MLPs) and Convolutional Neural Networks (CNNs) in several aspects. First, KAN's unique design is based on the Kolmogorov-Arnold theorem, introducing learnable univariate functions instead of fixed linear weights. This design allows KAN to apply dynamically adjustable activation functions on network edges, unlike traditional neural networks that use fixed activation functions at the nodes. Specifically, each weight parameter in KAN is represented by a univariate function, typically parameterized by spline functions. This architecture enhances the network's flexibility, enabling it to better adapt to different data patterns [5, 7].

In terms of parameter optimization, traditional neural networks focus primarily on fixed weights and biases. KAN expands the scope of optimization by introducing learnable activation functions. This means that during the optimization process, not only are the weights and biases of the network adjusted, but also the parameters of the activation functions. While this increases the complexity of training, it also provides greater flexibility, allowing KAN to more effectively capture complex data relationships [14].

Furthermore, traditional neural networks often require a large number of parameters and computational resources, especially in large CNNs. This is a significant limitation in resource-constrained environments. KAN, by using learnable univariate functions, significantly reduces the number of parameters. For example, Convolutional KANs (Conv-KAN) achieve high accuracy with significantly fewer parameters than traditional CNNs, effectively reducing computational costs [7]. This reduction not only improves computational efficiency but also enhances the model's scalability, making it more suitable for resource-constrained environments [5].

## 3.2 Advantages of KAN Networks in Handling High-Dimensional Data

KAN networks exhibit unique advantages when dealing with high-dimensional data. Because KAN uses learnable univariate functions instead of fixed weights, it can more flexibly adapt to the complex structures of high-dimensional data. Studies have shown that KAN achieves higher accuracy and efficiency in applications such as hyperspectral

image classification and time series analysis through a more flexible model architecture [5, 6]. This advantage makes KAN particularly effective in large-scale datasets and high-dimensional data processing.

# 3.3 Enhanced Accuracy and Interpretability of KAN Networks

The design of KAN not only improves model performance but also enhances interpretability. The fixed activation functions of traditional neural networks limit the understanding of the model's decision-making process. In contrast, KAN uses learnable activation functions, enabling researchers and users to more intuitively understand and interpret the internal mechanisms and decision-making processes of the model. This is particularly important for applications requiring high interpretability, such as medical diagnosis and financial forecasting [7]. Enhanced interpretability helps build trust and transparency in the model's decisions, especially in critical application areas.

To enhance the interpretability of KAN, the following strategies are introduced in its design:

- 1. **Sparsification:** As a preprocessing step, linear weights are replaced by learnable activation functions. The L1 norm of these activation functions, defined as the average amplitude of their  $N_p$  inputs, is used. However, the L1 norm alone is insufficient for sparsification and additional entropy regularization is required.
- 2. **Visualization:** By setting the transparency of the activation function  $\Phi_{l,i,j}$  proportional to  $\tanh(\beta A_{l,i,j})$  (where  $\beta = 3$ ), small-amplitude functions are ignored, allowing focus on important functions, thus enhancing interpretability.
- 3. **Pruning:** After training with sparsification penalties, the network is pruned to form a smaller subnetwork by removing all non-essential neurons. This not only optimizes the model structure but also improves interpretability.
- 4. **Symbolification:** An interface is provided to set some activation functions to specified symbolic forms, such as cos or log, by fitting affine parameters to pre-activation and post-activation samples, allowing outputs to approximate specific symbolic function transformations. This step further promotes symbolic expression and understanding of the model's decision-making process.

Several studies have shown that the architecture of KAN, by using learnable univariate functions, can more accurately capture complex data relationships and significantly improve model accuracy. For instance, Liu et al. demonstrated that KAN outperforms traditional methods in hyperspectral image classification, with notable improvements in accuracy and robustness [5]. Additionally, Dhiman's research indicated that KAN excels in time series forecasting, accurately capturing complex patterns and nonlinear relationships in the data [7]. Through the comprehensive application of these strategies, KAN not only enhances performance but also achieves significant improvements in interpretability.

# 4 Training and Optimization of KAN Networks

# 4.1 Training Process and Challenges of KAN Networks

The training process of Kolmogorov-Arnold Networks (KAN) is similar to that of other neural network models, typically employing the backpropagation algorithm. Initially, network parameters are initialized, followed by forward propagation to compute the output. The loss function is then used to measure the discrepancy between the predicted and actual results, and the backpropagation algorithm calculates the gradient of the loss function with respect to each parameter. Finally, parameters are updated using gradient descent or other optimization algorithms [7]. Since KAN's activation functions are learnable, the training process requires simultaneous optimization of both the activation functions on the edges and the weights between nodes. This process necessitates fine-tuned adjustments to ensure stability and convergence [14].

# 4.2 Techniques and Strategies Explored by Researchers During Training

To enhance the training efficiency and generalization ability of KAN, researchers have explored various techniques and strategies during the training process. For example, using regularization techniques such as Dropout, weight decay, and batch normalization can effectively improve KAN's training efficiency and generalization ability [5]. Dropout technique randomly discards a portion of neurons to prevent overfitting; weight decay controls model complexity by adding the L2 norm of weights to the loss function; and batch normalization standardizes inputs, improving the stability and speed of model training [7].

Moreover, recent studies have shown that combining advanced optimization algorithms, such as the Adam optimizer and stochastic gradient descent, KAN performs excellently when handling large-scale datasets [14]. The Adam op-

timizer combines momentum and adaptive learning rates to converge faster to the optimal solution, while stochastic gradient descent updates each mini-batch of data, significantly enhancing training efficiency [5].

# 4.3 Methods to Ensure Stability and Efficiency of the Training Process

- 1. **Using Regularization Techniques:** Techniques such as Dropout and weight decay can prevent overfitting and improve the generalization ability of the model [7].
- 2. **Batch Normalization:** Helps accelerate the training process and makes the model more stable during training [5].
- 3. **Optimization Algorithms:** Using advanced optimization algorithms, such as the Adam optimizer and stochastic gradient descent, can significantly enhance training efficiency and model performance [14].

# 5 Comparison between MLP and KAN

The Multi-Layer Perceptron (MLP) is one of the most fundamental structures in the field of deep learning. In this section, we will compare MLP and KAN in several aspect. Since KAN requires incorporating an external knowledge base, it results in a more complex time complexity[15]. In general, KANs exhibit potential across various fields; however, they consume more computational resources.

## 5.1 Performance on Noisy Functions

KAN seems to be a promising way to deal with data with noise. Zen et al [16] compare KAN and MLP based on 6 different irregular or nosy functions. Their research shows that, for some function, KAN has a better performance. However, on regular function noise, KAN performs worse than MLP, even though KAN converges more faster. For jumping function, MLP performs better. Shukla et al [17] compare KAN-based architectures and MLP for solving PDEs with noisy data. The result shows a similar tendency. They find that KAN has a better performance than MLP after specific parameter tuning.

#### **5.2** Time Complexity

KAN may take more time compared with MLP in the same task. After [16] comparing the time consumption by L-BFGS algorithm, Zen et al find that KAN spends more time in almost all task. Moreover, KAN even takes 100 times the time of MLP, which extremely limit its application to the real world. In the experiment done by Sasse and Farias [18], they use KAN based on B-spline activation function (Spline-KAN) for Federated Learning (FL) tasks. Their result show that although KAN does spends more time than MLP, which may take 1.36 times the time of MLP. However, this difference is not as significant as expected.

#### 5.3 Low-Data Training

KAN shows a worse performance than MLP when focusing on low-data regimes. Pourkamali-Anaraki [19] assumes that MLP has advantages than KAN when using limited labeled data after comparing the learnable parameters of the two. In general, KAN has more learned parameters. Zen et al [16] finds that after adding data, KAN will perform better in some specific tasks. However, it shows that MLP can be more accurate than KAN if the training is limited.

## 5.4 Reinforcement Learning

Conservative Q-learning (CQL) task comparison done by Guo et al[15] shows that pure MLP-based CQL model has the best performance. However, adding more hidden layers to the KAN actor did not significantly improve the model's performance.

# 5.5 Performance on Computer Vision

Cheon [20] validated the effectiveness of KAN in visual tasks on the MNIST, CIFAR10, and CIFAR100 datasets. The result shows that KAN has a better performance than MLP on CIFAR10, and CIFAR100 but slightly worse than the state-of-the-art ResNet-18. Bodner et al [20] create Convolutional Kolmogorov-Arnold Networks (Convolutional KANs) and validate the performance of Convolutional KANs against traditional architectures across Fashion-MNIST dataset. Their experiments show that Convolutional KANs reach the a similar level of accuracy with half parameters which demonstrate the potential of KANs in computer version field. Han et al [21] have proved that KAN has potential

in face recognition field compared with KAN and they propose 2 different variants. However, Tran et al [22] explore the limits of KAN on classification tasks. They claim that KAN exceed MLP despite theoretical advantages in accuracy and interpretability since KAN will consume more resources and have higher latency than MLPs. Their results show that MLP is still the better option when it comes to classification task. Moreover, Mohan et al [23] highlight that KAN is sensitive to hyperparameters and extremely demanding on computing resources and it need justify its structure to fit large computer vision problems.

#### 5.6 Performance on Tabular Data

Poeta et al [24] postpone a benchmarking study comparing MLP and KAN on tabular datasets. The results show that KANs have a higher  $F_1$  score and more accuracy, demonstrating robust in processing complex data. However, they also highlight the high cost of KAN.

#### 5.7 Performance on Time Series Problems

Vaca-Rubio et al [25] compare KAN and MLP in a real-world satellite traffic forecasting task. Their results show that KAN has less learnable parameters. The reduction in complexity shows that KAN can achieve higher accuracy with simpler and lighter structure.

**Performance on Dynamical Systems** Nehma and Tiwari [26] compare MLP and KANs in finding Deep Koopman operators for linearizing nonlinear dynamics. In their work, they construct a KANs-based deep Koopman framework and apply to the pendulum, the combined pendulum-cart system and an orbital Two-Body Problem (2BP) for data-driven discovery of linear system dynamics. Their results show that KANs is superior to MLP DNNs, learning 31 times faster, being 15 times more parameter-efficient, and predicting 1.25 times more accurately in the 2BP case. They claim KANs can help develop Deep Koopman Theory.

# 6 Application of KAN Networks

In this section, we will discuss the applications of KAN in different fields.

#### 6.1 Time Series

Kolmogorov-Arnold Networks (KAN) have shown significant potential in time series prediction. Time series prediction entails utilizing historical data to forecast future values and has extensive applications in areas such as financial market analysis, weather forecasting, and medical monitoring. KAN, with its unique architecture and flexible activation functions, can capture complex patterns and both short-term and long-term dependencies in time series data.

**Temporal Kolmogorov-Arnold Networks (TKAN)** T-KAN constructed by Genet and Inzirillo [27] is combined of RKAN (Recurrent Kolmogorov-Arnold) Network layers and Gating Mecanism. The special structure enables T-KAN to solve the complex time series problems and maintain long memory. In general, it combined RKAN and slightly modified LSTM, and its activation function can help capture complex nonlinearities.

Time Series Kolmogorov-Arnold Networks and Multivariate Time Series Kolmogorov-Arnold Networks (T-KAN and MT-KAN) Xu et al (2024) [28] propose T-KAN and MT-KAN model to solve time series prediction problems. T-KAN employs a two-layer (2-depth) network structure where each layer consists of spline-parametrized univariate functions. It is designed to handle univariate time series data. MT-KAN is a variant of T-KAN, which is designed to handle multivariate time series data. MT-KAN employs mechanisms to model cross-variable interactions, which allows it to exploit the relationships among different variables.

**Signature-Weighted Kolmogorov-Arnold Networks (SigKAN)** SigKAN is composed of SigLayer and KAN layer. Specially, the KAN layer is modified by Gated Residual Networks (GRN), which makes the model modulate the information flow during the learning task. The Learnable Path Signature layer (SigLayer) makes it possible to compute the path signatures for each path with learnable scaling. SigKAN can better understand and predict complex time series patterns and shows great dynamic adaptation [29]

**WormKAN** Xu et al (2024) [30] applied KAN in decoder and encoder, with a self-representation layer implemented as a 2-layer KAN. Thy compared the model with StreamScope, TICC, AutoPlait. The results show that WormKAN has higher  $F_1$  score and ARI. It shows potential in co-evolving time series tasks.

**HiPPO-KAN** Lee et al [31] integrate High-order Polynomial Projection (HiPPO) theory into the Kolmogorov-Arnold network (KAN) framework. They highlight that the model can help address the problem of time series forecasting in the context of cryptocurrency markets, specifically focusing on the BTC-USDT trading pair. Compared with other models, HiPPO-KAN with 500 window size has a smaller MAE, HiPPO-KAN with 1200 window size has a smaller MSE, which shows a better accuracy in time series tasks.

**KAN-AD** . Kolmogorov–Arnold Net-works (KAN) has potential to decompose the complex temporal sequences into different functions, which makes it easy to be controlled when training. However, this method may be influenced by local anomalies. Zhou et al [32] use the Fourier series to emphasize global temporal patterns, thereby mitigating the influence oflocal peaks and drops. Their evaluation shows that KAN-AD has a better efficiency and costs less time compared with state-of-art technologies.

#### 6.2 Interpretability and Symbolic Regression

Kolmogorov-Arnold Networks (KAN) provide enhanced interpretability compared to traditional neural networks, such as Multi-Layer Perceptrons (MLP)[33]. In this section, we will introduce some explainable models.

**Monotonic Kolmogorov-Arnold Network (MonoKAN)** Polo-Molina et al [34] construe a new structure of KAN which can enhance the model's interpretability. They replace the B-splines with cubic Hermite splines which has well-known sufficient conditions for monotonicity. experiments and mathematical reasoning demonstrated monotonicity. Since the momotonicity of the model is proved, the new structure is thought to be more explainable.

**KAN2CD** KAN2CD [35] is designed to enhance interpretability in two manners. The first method is to replace the MLP layer in CMD (cognitive diagnosis models). The second method uses KAN to deal with student embedding, exercise embedding and concept embedding and then the output will be combined and learned by KAN. Yang et al highlight that the learned structures of KAN make KAN2CD more explainable than traditional CMDs.

**Bayesian Kolmogorov Arnold Networks (BKANs)** Hassan [36] combines KANs with Bayesian inference and then tests the new model on 2 medical datasets. The results show that BKANs show great improvement in interpretability and accuracy compared with traditional deep learning models.

**CoxKAN** Knottenbelt et al [37] combine Cox Proportional Hazards Model and Kolmogorov Arnold Network for interpretable, high performance survival analysis, named as CoxKAN. Then they evaluate CoxKAN on 4 synthetic datasets and 9 real medical datasets. The results on 9 real medical datasets show that CoxKAN always has a better performance than original Cox Proportional Hazards Model. Moreover, CoxKAN can obtain symbolic formulas for the hazard function and visualizing KAN activation functions and visualize the activation functions, which show great interpretability.

**KAN-XGBoost** Amouri et al [38] introduce hybrid model consists of KAN and XGBoost algorithm. The hybrid model integrates the learnable function of KAN and high accuracy in classification task, show great accuracy and interpretability in the Intrusion Detection System. It has higher higher accuracy, precision, recall and F<sub>1</sub> score on N-BaIoT dataset compared with standalone MLP and KAN networks.

#### 6.3 Health and Medical Field

U-KAN Li et al [?] integrate KAN into the tokenization process after using Convolution Phrase to abstract features to enhance U-Net. Then, they extend the model to diffusion models. Their test on medical datasets BUSI and GlaS shows that U-KAN has a better compared with state-of-the-art segmentation models on three heterogeneous medical scenarios. Tang et al [39] apply U-KAN to 3D brain tumor segmentation using multi-modal MRI data including a variant called UKAN-SE. They compare the models with current models like U-Net, attention U-Net and so forth. The result show that U-KAN and UKAN-SE have better efficiency and accuracy with less training time.

KACQ-DCNN (Uncertainty-Aware Interpretable Kolmogorov-Arnold Classical-Quantum Dual-Channel Neural Network) Jahin et al [40] incorporates classical and dressed quantum models as a part of the hybrid dual-channel model. After comprehensive evaluating, they find that 4-qubit, 1-layer KACQ-DCNN outperforms 37 benchmark models, with a much better accuracy and higher  $F_1$ -score. They test the model on a consolidated dataset including 918 samples and shows great potential in heart disease diagnosis. They emphasize that the model incorporates uncertainty quantification and employs post-hoc explainability techniques, which enhance its interpretability and reliability in clinical settings.

**ECG-SleepNet** Aghaomidi and Wang present a normal approach to classify the different sleep stages. [41] They use KAN to distinguish the five sleep stages after collecting different biological signals. The best accuracy is about 81 percent, which shows great advance compared with previous models.

**MvKeTR (Multi-view perception Knowledge-enhanced TansfoRmer)** Deng et al [42] designed MvKeTR, a new framework which combines Multi-View Per-ception Aggregator (MVPA), Transformer and KAN to help generate CT report. In ablation experiment, they show that MvKeTR has great enhancement compared with previous frameworks.

**KAN-Mamba FusionNet** Agrawal et al [43] combine KAN with Mamba layers for medical image segmentation. In their experiments, they compared their framework on BUSI, Kvasir-Seg and GlaS datasets. They claim that their model outperforms the current state-of-the-art in both IoU and  $F_1$  scores.

#### 6.4 Computer Vision and Image Processing

**KAN-CUT** Mahara et al [44] replace the two-layer MLP with a two-layer KAN in the Contrastive Unparied Image-to-Image Translation (CUT) model. They use some well-known GAN models as baselines, including CycleGAN, MUNIT and so on. Their results show that KAN-CUT has a smaller FID score in Horse2Dog and Cat2Dog datasets. Moreover, they highlight that KAN-CUT can generate higher quality zebra images based on stripes, structure, and color.

**KAN-Block** In order to address the problems caused by uneven illumination and noise effects, Ning et al [45] design a KAN-block to introduce KANs into the U-Net structure in the low-light enhancement task. In their experiments, they choose LOLv1, LOLv2, and LSRW datasets and Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) as two full-reference distortion metrics. Additionally, they employ Learned Perceptual Image Block Similarity (LPIPS) and Fréchet Inception Distance (FID) as two perceptual metrics to evaluate the visual quality of the enhanced outcomes. Their results show that their method is able to recover image details and enhance quality. Moreover, their method shows strong generalization and robustness.

**RKAN** (**Residual Kolmogorov-Arnold Network**) Yu, Wu and Gui [46] integrates the Kolmogorov-Arnold Network (KAN) into the CNN framework as a residual element and then postpone RKAN block. Then, they test the model on some famous datasets including CIFAR-10, Food-101. Their results show that RAKN has potential to solve some challenging problems for traditional CNNs, or even Vision Transformers (ViT). However, they also mention the high cost of the model.

**PEP-GS** Jin et al [47] combine Multi-head Self-attention, KAN and Laplacian Pyramid Decomposition and propose a new framework PEP-GS. They claim that their framework show high accuracy in complex scenarios.

# 6.5 Graph Neural Network and Collaborative Filtering

**FourierKAN-GCF** Xu et al [48] replace the multilayer perceptron (MLP) with Fourier Kolmogorov-Arnold Network (KAN) as a part of the feature transformation during message passing in GCN. They test the model on MOOC and Anazon Video Games datasets and select BPR-MF and BUIR as baseline. The results shown that FourierKAN-GCF outperforms all baselines in two datasets across various metrics. They especially highlight that their method is easier to train and has representation power than MLPs

**Graph Kolmogorov–ArnoldNetwork (GKAN)** Carlo[49] extends Kolmogorov-Arnold Networks (KAN) to graph-structured data by introducing learnable functions to replace traditional GCN's fixed convolution. This flexible approach allows GKAN to adapt dynamically, enhancing its ability to process complex graph data. Experiments show GKAN outperforms traditional GCNs in tasks like node classification, social network, and molecular graph analysis, especially with large-scale and high-dimensional data.

**CF-KAN** Park et al [50] introduce KAN to Collaborative filtering (CF) part in recommender systems. They claim that the through the ability of KAN to learn nonlinear functions at the edge level, exhibit enhanced resistance to catastrophic forgetting compared to MLPs. In their experiments, they compare CF-KAN with CF-MLP on some real-word datasets. The results show that KANs outperform CF-MLP, are highly interpretable, scalable, and will be explored further in diverse recommendation domains.

#### 6.6 Physics-Informed Neural Networks and Engineering Applications

**DeepOKAN** Diab et al [51] introduce a new neural operators called DeepOKAN, using KANs rather than the conventional neural network architectures. In general, DeepOKAN has potential in solving various mechanical problems. Then they compare DeepOAKN with DeepONet. They claim that although DeepONet is effective on classical data-driven, DeepOKAN outperforms it.

**Kolmogorov-Arnold-Informed Neural Network (KINN)** In order to solve the problem caused by AI for PDEs, Wang et al [52] propose different PDE forms based on KAN instead of MLP, termed Kolmogorov-Arnold-Informed Neural Network (KINN) for solving forward and inverse problems. In their test, they compared KAN and MLP in strong, energy, and inverse forms of PDEs. The results show that KAN has higher accuracy and convergence speed than MLP in most PDE problems. They highlight that KAN is a promising method to solve PDEs. However, they claim that it is important to determine the grid size according to the problem's complexity and its long training time is still a problem.

**Physics-Informed Kolmogorov-Arnold Networks (PIKAN)** Shuai and Li [53] introduce a KAN-based physics-informed neural network (PINN) which is can efficiently and accurately learn dynamics within power systems. They replace the traditional MLP layers with KAN layers. PIKANs achieve a better accuracy in predicting power system dynamics with a smaller network size. The results show that PIKANs in accurately capturing the dynamics of power systems, which demonstrates a the bright feature of KAN in PINN.

**ChebPIKAN** Based on Physics-informed Neural Networks (PINNs) and Chebyshev polynomial, Guo et al [54] propose a new framework ChebPIKAN. They show the strong ability of the model in solving PDEs through numerous experiments. This model demonstrates strong potential in fields requiring complex and rapid computations like Fluid Mechanics.

**Separable Physics-Informed Kolmogorov-Arnold Networks (SPIKANs)** In order to solve the problem of slow training speed, Jacob, Howard and Stinis [55] introduce a new framework which combines Separable PINNs and KAN. The special design of the framework can separate the PDEs problems into different parts and use KAN payers to solve rather than traditional unstructured point-cloud used in PINNs. These improvements lead to a reduction in the time required to solve PDE problems.

# 6.7 Tabular Data

**TKGMLP** Zhang et al [56] propose a hybrid model called TKGMLP, which combines MLP and KAN and it is designed for large-scale financial tabular data. Moreover, they propose a new encoding method for financial numerical data. They claim that their model can enhance the prediction accuracy for tasks such as credit scoring.

**KACDP** (**Kolmogorov - Arnold Credit Dedault Predict**) Liu and Zhao [57] use KAN for personal credit risk prediction. They claim that their model has a better performance compared with traditional models. They thought that the non-linear property of KAN is the key and the model has great interpretability.

# 7 Current Research Progress

Kolmogorov-Arnold Networks (KAN) have achieved significant progress in various fields. Below are some recent important studies. In general, current studies mainly focus on the activation functions.

## 7.1 Other Variables of KANs

Chebyshev Kolmogorov-Arnold Network SS et al [58]improve KAN with the Chebyshev polynomials, named as Chebyshev KAN (Polynomial-based Kolmogorov-Arnold Network). Chebyshev polynomials, which is famous of approximation properties, particularly rapid convergence and numerical stability, improve accuracy and efficiency of the KAN. In their experiments, they claim that Chebyshev KAN exceeds MLP in MNIST datasets and shows tremendous potential in nonlinear problems. Based on Chebyshev KAN, Mostajeran and Faroughi [59] propose EPIcKANs (Elasto-Plasticity Informed Chebyshev-based Kolmogorov-Arnold Network). In their work, they improve traditional elasto-plastic constitutive models by Chebyshev KAN. In their experiments, they test the ability of EPIcKANs in several mechanical behavior of geotechnical materials tasks. The results show that EPI-cKANs can be an alternative model in non-linear materials behavior various engineering and scientific domains.

**Wav-KAN** (**Wavelet Kolmogorov-Arnold Networks**) Bozorgasl and Chen [60] incorporating wavelet functions into the Kolmogorov-Arnold network structure, enabling the model to capture both high-frequency and low-frequency components of the input data efficiently. Compared with Sql-KAN and traditional MLP, Wav-KAN shows great accuracy, faster training speeds, and increased robustness. They highlight Wav-KAN's promise in developing interpretable and high-performance networks.

**PointNet-KAN** Kashefi [61] introduces PointNet-KAN which replaces the MLP layers in PointNet with KAN. In the experiments, PointNet-KAN shows competitive performance to PointNet in both classification and segmentation tasks. Kashefi claim that the KANs is capable of being applied to advanced point cloud processing architectures.

## 7.2 Other Application and Study of KANs

#### 7.3 Geographic Information Science

Liu et al [62] apply to the problem of baseflow identification. They highlight that KANs enhance the interpretability of machine-learned hydrological models and exceed the state-of-the-art existing semi-empirical models in hydrological processes. Cheon [63] integrates Kolmogorov-Arnold Network (KAN) and Convolutional Neural Network (CNN) models including VGG16 and so forth. After experiments on EuroSAT dataset, Cheon finds that ConvNeXt paired with KAN, named KCN, shows the best performance and might be a promising alternative for efficient image analysis in the RS field.

**Computer Vision** Yu et al [64] explore the KANs for image quality assessment by comparing KANs with different activation functions. After rigorous and detailed comparative experiments, they introduce TaylorKAN with mid-level feature input, which shows great performance on 3 realistic image databases (BID2011, CID2013 and CLIVE). Cang et al [65] compared KAN with its variant, Convolutional KAN (CKAN), which are popular in this field. However, they claim that CKAN underperforms traditional CNNs due to low generalization, while KAN, despite strong fitting, also lacks generalization, making it unsuitable for replacing the final layer with an NLP layer.

## **Medical Field**

**CEST MRI (Chemical Exchange Saturation Transfer Magnetic Resonance Imaging)** Wang et al [66] demonstrate that KAN can be a promising way to analysis CEST MRI for the first time. In their experiment, they find that KAN exceed MLP in extrapolating the CEST fitting parameters although it need more time to train. Moreover, they find that Voxel-wise correlation analysis show that the 4 CEST fitting parameters generated by KAN have a higher Pearson coefficients than the MLP results, which shows the advance of KAN.

**Neuroanatomy** In order to solve the problem brought by 3-hinge gyrus identification, Chen et al [67] introduce a new framework built with KANs. In their experiments, they show the strong ability in typology. They claim that the framework can play an important role in neuroanatomy field.

# 7.4 Model Integration and Application Expansion

**KAT** (**Kolmogorov–Arnold Transformer**) Transformer, known as the cornerstone of mordern deep learning, utilizes MLP as the basic block. Yang and Wang [68] replace MLP layers in transformer with KAN, called KAT (Kolmogorov–Arnold Transformer). They claim that their innovation exceed traditional MLP transformer in some vision tasks, including image recognition, object detection, and semantic segmentation.

**KAMoE** Based on Gated Residual Kolmogorov-Arnold Networks (GRKAN) Inzirillo and Genet [69] introduce KAMoE, which is a novel framework for Mixture of Experts (MoE). They claim that KAN can be a tool to enhance Multi-task Learning tasks although its standalone is still under discussion.

## 7.5 Robustness and Generalization

Alter, Lapid and Sipper[?] test the robustness of KAN under adversarial conditions, especially, they put emphasis on image classification tasks. After experiments, they claim that KANs may be particularly effective in scenarios where larger models are feasible and robustness is critical. However, after comparing the generalization of MLP and KAN, they highlight that KAN has low transferability of information, which show the different structure between KAN and MLP.

## 7.6 Theoretical Analysis

Gao and Tan [70] studied gradient descent (GD) and stochastic gradient descent (SGD) of KAN. They claim that using SGD to optimize KAN can be used to enhance the performance on some machine learning tasks. Moreover, they analysis the global convergence of GD and SGD for physics-informed KANs, which might be used to optimize physics-informed KANs.

Wang et al [71] carefully compared KAN and MLP from a theoretical perspective. From the perspective of approximation, MLP and KAN is very similar sharing parameterize similar classes of functions. However, they find that KANs lack the spectral bias toward low frequencies that is characteristic of MLPs. They claim that their research results can contribute to computing applications like solving PDEs.

# 7.7 Improvements and Optimizations

**Rational KAN** (**rKAN**) Afzalaghaei et al [72] proposed rKAN, which models using rational function bases. This method employs Padé approximations and rational Jacobi functions, significantly improving KAN's performance in regression and classification tasks. rKAN enhances model accuracy and computational efficiency through improved activation functions and more efficient parameter update mechanisms.

**ReLU-KAN** Qiu et al [73] replace basis spline functions (B-Spline function) with singly matrix addition, dot production and ReLU activation functions. They claim that their new structure of KAN can help handle the problem of catastrophic forgetting and its backpropagation is much faster efficient GPU utilization. Also, they mention that ReLU-KAN demonstrates enhanced fitting performance for complex problems, which exceed traditional KAN.

**Kolmogorov-Arnold Networks Using Sinusoidal Activation Functions (SineKAN)** Reinhardt, Dinesh and Gleyzer [74] utilize sinusoidal activation functions as B-Spline function. In their experiments, they compare SineKAN with B-SplineKAN on MNIST dataset. They claim that The SineKAN model outperforms B-SplineKAN in performance, scalability, and speed, achieving up to 9x faster benchmarks.

**Unbound Kolmogorov-Arnold Network (UKAN)** Moradzadeh et al [75] introduce the Unbound Kolmogorov-Arnold Network (UKAN), which combines MLP layers with KANs along with an efficient GPU implementation. They claim that UKAN can reduce time complexity. In their experiments, they test their model on Moon and MNIST datasets. The results show that UKAN get almost 100 percent accuracy.

**Higher-order-ReLU-KANs** (**HRKANs**) So and Yung [76] introduce HRKANs, which uses a higher-order-ReLU as the activation function. In their experiments, they exam URKANs on two famous and representative PDEs linear Poisson equation and nonlinear Burgers' equation with viscosity. They claim that URKANs achieve superior fitting accuracy, enhanced robustness, and faster convergence.

**Selectable KAN (S-KAN)** Yang et al [77] introduce S-KAN, which can select activation functions in the pool. Also, they expand S-KAN and propose an activation space selectable Convolutional KAN (S-ConvKAN). They claim that the performance of S-KAN is significantly enhanced by using multiple different learnable nonlinear activations. Also, they find that S-COnvKAN is suitable for general computer vision image tasks.

**PowerKAN** In order to solve the problems caused by the high time complexity of KAN, Qiu et al [78] introduce PowerKAN. They claim PowerKAN accelerates the speed of computing in approximately the same training time as MLP and shows stronger expressive power than KAN.

Constraint Informed Kolmogorov-Arnold Networks (CIKAN) Kim et al [79] combine Constrained-Informed Neural Network (CINN) with KAN and propose CIKAN. They validate CIKAN-TSG through simulations of constrained spacecraft rendezvous on elliptic orbits, comparing it with MLP-CINNs and standard TSGs.

**Kolmogorov-Arnold Networks with Interactive Convolutional Elements (KANICE)** Ferdaus et al [80] combine the Interactive Convolutional Blocks (ICBs) of RNN and KAN linear layers with CNN framework, which can be used to computer vision field. Compared with traditional frameworks, they show that their model is more accurate. Also, they propose a new version of KANICE with less parameters but has almost the same accuracy.

# **8 Future Research Directions**

#### **8.1 Potential Improvements**

**Structural Optimization** Further optimization of KAN structures is an important direction for future research. Existing studies have shown that learnable univariate activation functions significantly enhance model flexibility and performance. However, there is still much room for optimization. For instance, Afzalaghaei and Kiamari (2024) proposed improving activation function representation capabilities by introducing rational function bases (rKAN), thereby enhancing model accuracy and computational efficiency in regression and classification tasks [81]. Future research can further explore the introduction of other function bases and how to adaptively select the best activation functions for different tasks.

**Training Method Improvements** Improving training methods will also be a key research direction. Current research shows that adversarial training (KAT) can significantly enhance model robustness [82]. Future research can explore more training strategies, such as hybrid adversarial training, transfer learning, and self-supervised learning, to further improve model performance in handling high-noise data and small sample data.

**Parallel Computing and Hardware Acceleration** Given the high computational complexity of KAN, future research could focus on parallel computing and hardware acceleration technologies. For example, utilizing Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs) for model acceleration, or designing dedicated hardware architectures to enhance KAN's computational efficiency.

## 8.2 New Application Scenarios

**Medical Diagnosis** The successful application of KAN in hyperspectral image classification indicates its great potential in medical diagnosis. For instance, KAN can be applied to medical image analysis, improving disease detection and diagnosis accuracy by capturing complex spatial-spectral patterns [83].

**Financial Prediction** KAN's ability to capture nonlinear relationships provides broad application prospects in financial market prediction. Future research can explore KAN's application in stock price prediction, risk management, and quantitative trading, modeling complex market dynamics to enhance prediction accuracy and decision support capabilities [6].

**Environmental Monitoring** Hyperspectral imaging has important applications in environmental monitoring, such as land use classification, water quality monitoring, and weather forecasting. KAN's advantages in handling high-dimensional and complex data make it an ideal tool for environmental monitoring [84].

# 8.3 Interdisciplinary Combinations and Research Opportunities

**Integration with Quantum Computing** Quantum computing is emerging as a new research hotspot. The combination of KAN and quantum computing (KANQAS) promises to significantly enhance the efficiency and performance of quantum algorithms. Future research can explore how to utilize the powerful computational capabilities of quantum computing to further optimize KAN's training and inference processes [5].

**Integration with Bioinformatics** Bioinformatics data are complex and high-dimensional. KAN's flexibility and strong modeling capabilities hold great potential in genomics, protein structure prediction, and biological network analysis. Future research can explore KAN's application in bioinformatics, advancing research in the life sciences [5].

**Integration with Physics** KAN's application in symbolic regression demonstrates its potential in the field of physics. Future research can further explore KAN's application in discovering physical laws, simulating physical processes, and optimizing experimental designs, driving innovation in physics research [5, 6].

KAN 2.0 and Adversarial Robustness Recent advancements like "KAN 2.0: Kolmogorov-Arnold Networks Meet Science" by Liu et al. (2024) provide new tools and methodologies that could significantly enhance KAN's application in scientific discovery, particularly in symbolic regression. On the other hand, the study "On the Robustness of Kolmogorov-Arnold Networks: An Adversarial Perspective" by Alter et al. (2024) emphasizes the importance of further improving KAN's robustness against adversarial attacks, which is critical for its application in security-sensitive areas such as finance and healthcare. Future research should focus on integrating these advancements to develop more robust, efficient, and versatile KAN models[85, 86].

# 9 Conclusion

Through a comprehensive review of Kolmogorov-Arnold Networks (KAN), we have gained a thorough understanding of its theoretical foundations, architectural design, application scenarios, and current research progress. KAN, with its unique architecture and flexible activation functions, excels in handling complex data patterns and nonlinear relationships, showcasing broad application potential.

Firstly, KAN's theoretical foundation, derived from the theorems of Kolmogorov and Arnold, endows KAN with exceptional performance in data fitting and solving partial differential equations (PDEs). Secondly, KAN's architecture, by introducing learnable univariate functions to replace fixed activation functions in traditional neural networks, enhances model flexibility and adaptability while also improving interpretability. This makes KAN particularly valuable in fields requiring high interpretability, such as medical diagnosis and financial prediction.

In specific applications, KAN has demonstrated significant advantages in symbolic regression, time series prediction, graph-structured data processing, and hyperspectral image classification. Current research advancements show that researchers are continuously optimizing KAN's architecture and training methods, improving its performance in various tasks. Future research directions include further optimizing KAN's structure and training methods, exploring its potential in new application scenarios such as medical diagnosis, financial prediction, and environmental monitoring, and investigating its interdisciplinary combinations with fields like quantum computing, bioinformatics, and physics.

These research directions will not only further KAN's development but also bring new breakthroughs to the fields of deep learning and data analysis. In summary, as an emerging neural network architecture, KAN exhibits tremendous research and application potential through its theoretical foundation, flexible architecture, and broad application prospects. With continuous optimization and expansion, KAN is expected to play an increasingly important role in future scientific research and practical applications.

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