Petrol Hizmetleri Borsa Yatırım Fonu (ETF) Tahmini için Gramian Açısal Alanın Evrişimsel Sinir Ağı Analizi

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Convolutional Neural Network Analysis of the Gramian Angular Field for Oil Services Exchange Traded Fund (ETF) Prediction

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Öz

Petrol fiyatlarının tahmini, alınacak ekonomik kararlar ve oluşturulacak mali politikalar açısından hem ülkeler hem de şirketler için önemlidir. Ancak finansal fiyat dalgalanmaları doğası gereği doğrusal olmayan, karmaşık ve belirsizdir. Bu nedenlerden dolayı petrol fiyatlarının tahmini zor bir problemdir. Literatürde, petrol fiyatlarını tahmin etmek için istatistiksel ve makine öğrenimi yöntemleri kullanılmıştır. Ancak bu çalışmaların çoğunda petrol fiyatları genellikle zaman serisi olarak temsil edilmiştir. Bu çalışmada, petrol borsa yatırım fonu (ETF) verileri, görüntülerin temsil gücünden faydalanmak için Gramian Açısal Alan (GAF) yöntemi kullanılarak 2 boyutlu görüntü olarak temsil edilmiş ve daha sonra bu görüntü veri kümelerini analiz etmek için AlexNet ve VGG16 evrişimsel sinir ağı (CNN) mimarileri kullanılmıştır. Mevcut ve önerilen GAF-AlexNet ve GAF-VGG16 modellerinin performanslarını test etmek için enerji şirketlerine yatırım yapan bir fon olan VanEck Petrol Hizmetleri ETF'sine (OIH) ait 2016 ve 2022 dönemlerini kapsayan bir veri kümesi kullanılmıştır. Deneysel değerlendirmeler, önerilen modellerin umut verici sonuçlar verdiğini göstermektedir. Bulgular, tahmin modelinin bir ticaret sistemine entegre edilmesinin, araştırmacılara ve yatırımcılara bir karar destek sistemi olarak değerli bilgiler sağlayabileceğini göstermektedir.

Anahtar Kelimeler: *Derin Öğrenme, Zaman Serisi Analizi, ETF, Gramian Açısal Alan (GAA), Fiyat Tahmini.*

Abstract

Prediction of oil prices is important for both countries and companies in terms of economic decisions to be made and financial policies to be created. However, due to the nature of financial price fluctuations, they are non-linear, complex, and uncertain. Because of this reasons, prediction of oil prices is a difficult problem. In the literature, statistical and machine learning methods have been used to predict oil prices. However, in most of these studies, oil prices were usually represented as time series. In this study, oil services Exchange-traded fund (ETF) data is represented as a 2D image using Gramian Angular Field (GAF) method, in order to benefit from the representation power of images and then AlexNet and VGG16 convolutional neural network (CNN) architectures are used to analyze this image datasets. To test the performances of existing and the proposed GAF-AlexNet and GAF-VGG16 models, a dataset covering period of 2016 and 2022 belonging to the VanEck Oil Services ETF (OIH), a fund that invests in energy companies, was used. Experimental evaluations show that the proposed models gave promising results. The findings suggest that integrating the predictive model into a trading system can provide valuable insights to researchers and investors as a decision support system.

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1. INTRODUCTION

Oil, which is one of the main energy sources, is important for industrialization and trade. However, fluctuations in oil prices affect the economic growth and financial stability of countries and companies. For this reason, the prediction of oil prices is crucial for the risk management and economic planning of both the country and the companies. However, this is a difficult task because financial price movements are inherently nonlinear, complex, and uncertain.

The methods used in the literature to predict financial price movements can be divided into two categories: statistical and machine learning methods. Some of the statistical methods used are the autoregressive integrated moving average model (ARIMA) (Zhao & Wang, 2014; Moshiri & Foroutan, 2006), generalized autoregressive conditional heteroscedasticity model (GARCH) (Hou & Suardi, 2012), vector autoregressive model (VAR) (Ramyar & Kianfar, 2017) and autoregressive fractional integrated moving average model (ARFIMA) (Pumi et al., 2019; Abdollahi & Ebrahimi, 2020). However, the performances of statistical methods have been limited due to the complexity of the datasets (Moshiri & Foroutan, 2006). Today, machine learning methods have gained importance due to their ability to model nonlinear and complex structures. For this purpose, artificial neural network (ANN) (Moshiri & Foroutan, 2006; Barunik & Malinska, 2016; Yu, Wang, & Lai, 2008), support vector machine (SVM) (Xie, Yu, & Xu, 2006; Fan et al., 2016), fuzzy inference system (ANFIS) (Abdollahi & Ebrahimi, 2020; Abd Elaziz, Ewees, & Alameer, 2020; Salamai, 2023), convolutional neural network (CNN) (Sezer & Ozbayoglu, 2018), and recurrent neural network (RNN) (Rather, Agarwal, & Sastry, 2015) methods are used. For time series analysis, CNN models can be utilized in different architectures, namely 1D-CNN and 2D-CNN. 1D-CNN models have yielded successful results, particularly in recognizing local patterns within time series (Srinivasamurthy, 2018; Estebsari & Rajabi, 2020; Sarıkoç & Celik, 2025). Nevertheless, the superior performance of CNN architectures stems from their ability to recognize patterns in 2D images. Studies have shown that converting time series data into 2D representations with spatial features can lead to more successful prediction results than using 1D data (Wu et al., 2018; Estebsari & Rajabi, 2020; Paheding et al., 2022). This suggests that while 1D data may be limited in capturing complex and long-term relationships, the global patterns obtained from 2D transformation methods can offer much stronger information representations for these long-term relationships (Srinivasamurthy, 2018; Shahid et al., 2022). Although 2D-CNN models achieve more successful results in prediction accuracy than 1D-CNN models by capturing long-term relationships, this success comes at the cost of higher computational expenses and longer training times (Shahid et al., 2022; Paheding et al., 2022). In the literature, most of the studies used time series representations of oil price data (Lertthaweedech, Kantavat, & Kijsirikul, 2022; Liu et al., 2019; Zhang et al., 2023), and there are limited studies that use image representations (Wang & Oates, 2015; Estebsari & Rajabi, 2020; Chen & Tsai, 2020) of oil price data (Sezer & Ozbayoglu, 2018; Naftali, Tucker, & Manuela, 2021; Arratia & Eduardo, 2020; Barra et al., 2020). Sezer & Ozbayoglu (2018) converted 15 technical indicators into an image for a 15-day period by using technical indicators in their studies and performed a three-class estimation process using the CNN-TA model. Naftali, Tucker, & Manuela (2021) converted time series data into candlestick images and examined its effect on forecast performance. Arratia & Eduardo (2020) used RP images to predict the direction of the index price in the next month by using 12 months of historical information from the S&P 500 index and proposed the Conv2D+RP model. Barra et al. (2020) converted the time series of the S&P 500 index into Gramian angular field (GAF) images and predicted the market behavior using a CNN. Wu et al. (2023) showed that 2D transformations such as RP, GASF, GADF, and MTF improve clustering performance in clustering financial time series. The study is important in terms of showing that 2D transformation is a powerful tool not only for forecasting but also for data analysis. Chauhan et al. (2023) demonstrated that 2D-GAF and 2D-MTF transformations can be applied to CNN models such as VGG16, ResNet50, InceptionV3, MobileNetV2, and Xception to predict financial data. Pandey et al. (2025) investigated the effectiveness of 2D-MTF image transformation on Random Forest and CNN models in stock price prediction. The study emphasised that the 2D-MTF transformation achieved better results than standard time series methods by transforming time series data into more meaningful information for the models. Long et al. (2025) tried to optimise the transfer learning process using 2D-GAF image transformations. The authors researched architectures such as DNN and LSTM and emphasised that 2D-GAF-based similarity functions reduce prediction errors compared to traditional similarity functions, while 2D-GAF transformations improve model performance in transfer learning.

The transformation of financial time series into 2D image objects for prediction using CNN models represents a novel research area for researchers. While the literature on this topic is rapidly growing, finding studies focusing on financial time series with themes related to oil and energy can be challenging. We aim to address this gap in the field. Furthermore, we present a framework for using Gramian Angular Fields (GAF) to convert time series from a unique financial dataset (OIH ETF) into 2D data for deep learning models. By demonstrating the applicability of the rich information representations—the 2D-GAF images—on advanced CNN architectures without training from scratch, we are opening new doors for researchers. In this study, a one-dimensional time series array consisting of the VanEck Oil Services ETF (OIH), a fund investing in energy and oil companies, was converted into 2D images using the GAF method (Chen & Tsai, 2020), and then the AlexNet and VGG16 CNN architectures were used to analyze these image datasets.

The rest of the paper is organized as follows. Section 2 presents the dataset, the GAF and CNN methods, and the proposed framework. Section 3 presents the experimental evaluation, and Section 4 presents the conclusion and future work.

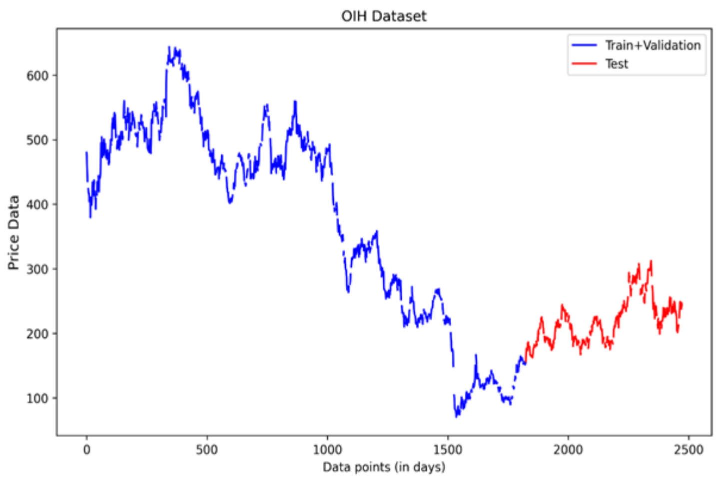
2. MATERIALS AND METHODS

In this section, first, the dataset is introduced; then, the details of the GAF method and the CNN model are given; and finally, the proposed methods are introduced

2.1. Dataset

In this study, VanEck Oil Services ETF (OIH) data were used. The Fund invests in the stocks of companies operating in the publicly traded energy, energy equipment and services, oil and gas drilling, oil and gas equipment, and services sectors of the United States. OIH fund data are collected from kibot.com (Kibot, 2023). Within the scope of the study, the date, time and closing values of the data were used. The data contain approximately 655000 time points (in minutes) from 04.01.2016 to 14.10.2022. In this study, 75% of the data belonging to the 2016 and 2020 periods were used as training and validation datasets, and 25% of the data belonging to the 2021 and 2022 periods were used as test datasets for deep learning models (Figure 1).

Figure 1. Visualization of the training+validation and test datasets



2.2. Gramian Angular Field (GAF)

In the literature, there are various methods, such as the MTF, RP and GAF methods, for converting time series to 2D images (Wang & Oates, 2015; Estebsari & Rajabi, 2020; Ozkok & Celik, 2021; Ozkok & Celik, 2023). GAF, which was proposed by Wang and Oates, is a time series coding method that allows time series to be represented in a polar coordinate system rather than in Cartesian coordinates (Wang & Oates, 2015). GAF methods are divided into two methods: the Gramian Total Angular Area (GASF) and the Gramian Difference Angular Area (GADF). To generate the GAF images, the time series need to be scaled. For this, the mean is scaled in the [-1, 1] range by normalization, with the time series shown as X={x1, x2, x3, …, xn} (Equation 1).

$$\tilde{x}^{i} = \frac{(x_i - \max(X)) + (x_i - \min(X))}{\max(X) - \min(X)} \tag{1}$$

The angular cosine of the single components of the resulting scaled time series is calculated and converted to a polar coordinate system as in (Equation 2).

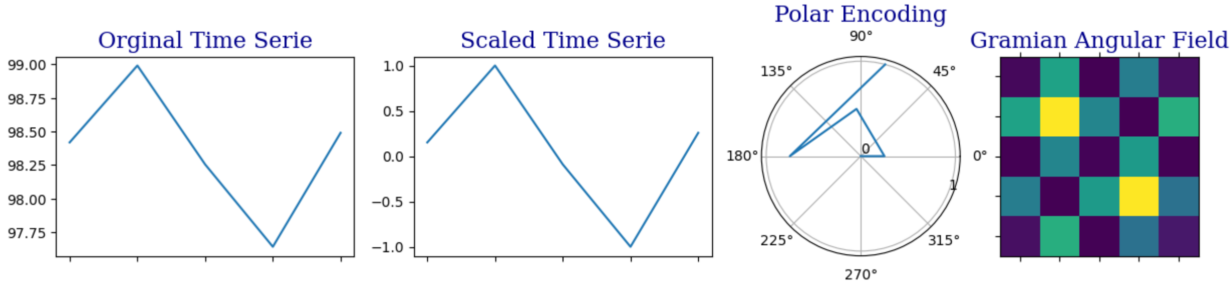
$$\begin{bmatrix} \theta_i = \arccos(\tilde{x}_i), & \tilde{x}_i \in \tilde{X} \\ r_i = \dfrac{i}{N}, & \text{with } t_i \leq N \end{bmatrix} \tag{2}$$

Then, the sum or difference values between the time series points are calculated, and optionally, GASF and GADF image objects are formed (Equation 3).

$$\begin{aligned} GASF &= \left[\cos(\theta_i + \theta_j)\right] = \tilde{X} \cdot \tilde{X} - \sqrt{1 - \tilde{X}^{2\prime}} \cdot \sqrt{1 - \tilde{X}^{2}} \\ GADF &= \left[\sin(\theta_i + \theta_j)\right] = \sqrt{1 - \tilde{X}^{2\prime}} \cdot \tilde{X} - \tilde{X} \cdot \sqrt{1 - \tilde{X}^{2}} \end{aligned} \tag{3}$$

In this study, we used the GADF format proposed by Barra et al. (2020). Figure 2 shows a simple time series plot of 5 temporal data points, a scaled plot, a polar coordinate system view, and a coded form in the GAF image matrix. Additionally, this sequential view from left to right represents the stages in which the GAF image objects are acquired.

Figure 2. Visualization of the stages in which the GAF image objects were acquired

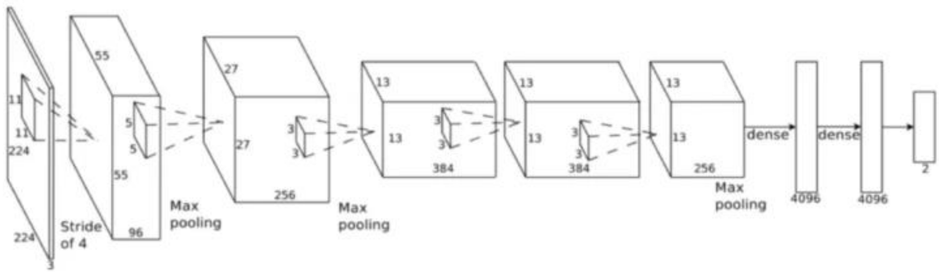


2.3. Convolutional Neural Network (CNN)

CNN models have become very popular due to their success in pattern recognition, classification, and natural language processing (Ozkok & Celik, 2021; Ozkok & Celik, 2023; LeCun, 2023; Thakkar & Chaudhari, 2021; Krizhevsky, Sutskever, & Hinton, 2012; Simonyan & Zisserman, 2014; Kilicarslan, Celik, & Sahin, 2021). They are generally used in image recognition problems (Sezer & Ozbayoglu, 2018). Unlike ANNs, they can use automatic feature extraction mechanisms. Therefore, they are suitable for extracting complex patterns from nonlinear information (Krizhevsky, Sutskever, & Hinton, 2012). A CNN consists of five layers: input, convolution, pooling, fully connected, and output layers. The convolution layer learns patterns via a technique similar to that used by the human eye. In this layer, features are extracted with the help of filters that slide horizontally and vertically on the input array. Deep learning models can have more than one convolution layer, and in this case, more features can be extracted. The pooling layer, similar to the convolution operation, is performed by sliding smaller filters on the feature maps and is used to reduce the number of features, that is, the complexity of the CNNs. The fully connected layer works like a simple ANN, and in this layer, all neurons are interconnected. It provides a generalization of patterns obtained by the convolution and pooling layers, and its output represents the probability of a class.

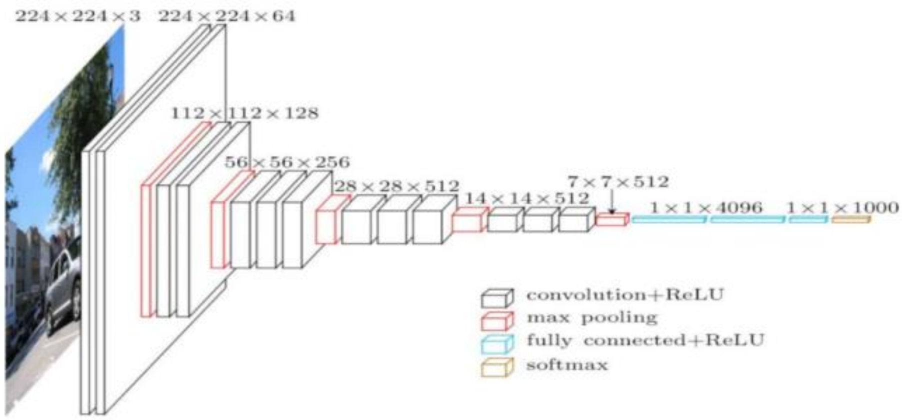
In this study, two CNN architectures, AlexNet (Simonyan & Zisserman, 2014) and VGG16 (Kilicarslan, Celik, & Sahin, 2021), were used. AlexNet has an architecture with pooling and activation layers between 5 convolution layers and 3 fully connected layers (Figure 3). The VGG16 architecture has a total of 16 layers, with 13 convolution layers and 3 fully connected layers (Figure 4) (Kilicarslan, Celik, & Sahin, 2021). Among these layers are pooling layers, as in AlexNet. Unlike AlexNet, the filter sizes in VGG16 are fixed at 3x3.

Figure 3. AlexNet CNN architectures used in the study



Reference: Simonyan & Zisserman (2014).

Figure 4. VGG16 CNN architectures used in the study

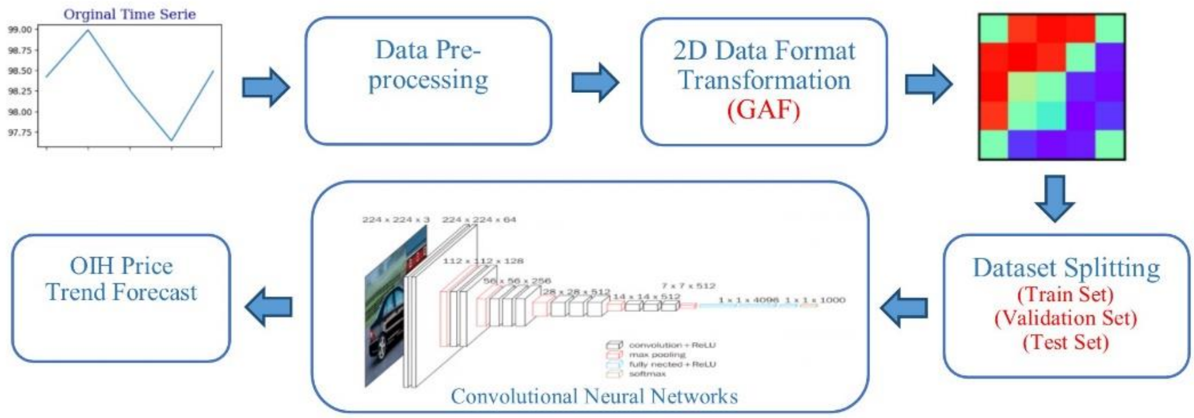


Reference: Kilicarslan, Celik, & Sahin (2021).

2.4. Proposed Method

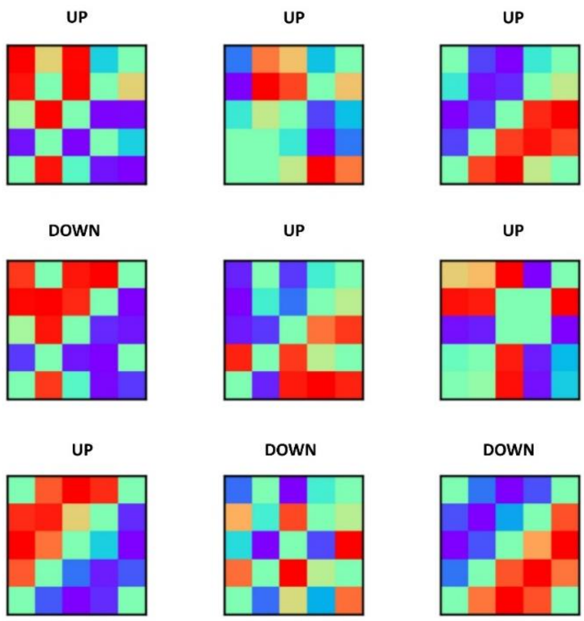
The use of CNNs for forecasting financial time series, which involves converting them into two-dimensional (2D) image objects, has emerged as a new research area of interest for researchers in recent years. While the number of studies in this field is increasing rapidly, there is a relative scarcity of research focusing on specific sectors, such as oil and energy. This study aims to predict the price series of the OIH index, which invests in the oil and energy sector, by converting them into 2D images. To this end, we utilize a CNN-based model presented in the literature that has been successfully applied to different time series.

Figure 5. The prediction framework used in the study



In this study, first, time series were converted into 2D images using the GAF method; then, the image dataset was divided into training, validation, and test sets; and finally, CNN models were used to predict the price of OIH. The framework of the study is presented in Figure 5.

Figure 6. An example representation of selected images and labeling information from the 2D dataset



The resulting OIH dataset comprises a feature set of 7 columns and 655000 rows in minutes. By making relevant calculations and creating approximately 2500 data points, we converted the data set of approximately 7 years, covering 2016-2022, into daily data. We removed the periods outside the working hours of the markets and holidays from the dataset and normalised the dataset. We converted the normalised data into 2D images using the GADF method. After these operations, we obtained 1690 image objects.. Each GAF image is provided with 224x224 resolution in accordance with CNN architectures. The aim is to predict the price direction of the next day from the price information 5 days prior, so image labeling operations were carried out in this direction. This study divided the dataset into two classes using "up" and "down" class labels, indicating two different price directions. In the next step, 75% of the OIH dataset is allocated for training (66% training and 9% for validation), and 25% for the test dataset (Demirezen et al., 2021). An example representation of selected imagery and label information from the dataset obtained after the 2D image transformation in the scope of the study is presented in Figure 6.

In machine learning, we develop prediction systems through training and testing on labeled or unlabeled datasets. A consensus suggests that the probability distributions of the training and test data should be balanced. During the training of a CNN model, we initialize the weights of each convolutional layer with values sampled from a normal distribution with a slight standard deviation and a zero mean (Shahid et al., 2022). However, with a unique dataset from financial markets, it is often challenging to meet these conditions, and we find training a CNN from scratch challenging. This is because (i) it requires a large amount of labeled training data for optimal convergence; (ii) training processes are time-consuming; (iii) there is a high risk of overfitting; and (iv) model optimization requires specialized expertise (Shahid et al., 2022). Transfer learning, however, allows us to use different datasets for training and testing, which can help overcome these challenges. We widely use advanced CNN architectures for various classification problems in the literature through transfer learning and pre-trained models. We selected two distinct CNN architectures for our study, one shallow (AlexNet) and one deep (VGG16). This allowed us to examine the performance of 2D-GAF transformations across CNN architectures of different depths.. The AlexNet architecture output is adapted to be 2 classes, density drop layers are added after the fully connected layers, and the dropout ratios are set to at least 0.5. In this study, the VGG16 model was applied together with the transfer learning method. Transfer learning is the process of transferring the knowledge gained from a similar problem previously learned to the model for a new problem. Due to the information obtained from previous learning, it will be possible to perform the learning process faster with less training data and with greater accuracy. The VGG16 model using the transfer learning method was trained only for fully connected layers. To do this, the model was first subjected to global mean pooling and then batch normalization. The number of neurons in the fully connected layers is set to 256.

In this study, the models that combined GAF with AlexNet and VGG16 were named GAF-AlexNet and GAF-VGG16, respectively.

3. RESULTS AND DISCUSSION

The performances of the proposed GAF-AlexNet and GAF-VGG16 models were compared with those of studies in the literature. The metrics of accuracy (Equation 4), precision (Equation 5), retrieval (Equation 6), and F1-score (Equation 7) were used for comparison.

$$\text{Accuracy} = (TP + TN)/(TP + FN + TN + FP) \tag{4}$$

$$\text{Precision} = TP/(TP + FP) \tag{5}$$

$$\text{Recall} = TP/(TP + FN) \quad (6)$$

$$\text{F1 score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \quad (7)$$

In the equations, TP, TN, FP, and FN represent the number of true positives, true negatives, false positives, and false negatives, respectively. The study was carried out in Python on the Google Colab platform. The pyts-python package was used to convert the time series of the OIH dataset to 2D-GAF images, and Keras/TenserFlow libraries were used for deep learning. The models were run on a machine with an Intel Core i7 processor at 2.50 GHz and 32 GB of RAM.

3.1. Experiments

In this study, several attempts were made to optimize the hyperparameters of deep learning models. Fully connected layers were obtained with values between 256-256 and 4096-4096 for GAF-AlexNet and between 256-256 and 512-512 for GAF-VGG16. For the dilution ratio, values between 0.1 and 0.5 were tested in both models, and the parameter values that gave the best results were selected The hyperparameters used in these fine-tuning processes and the values of these parameters are shown in Table 1. In addition, Keras-Callback functions, EarlyStopping (parameters used: monitor="val_loss", mode="min", patience=10) and ReduceLROnPlateau (parameters used: monitor="val_acc", patience=3, factor=0.5, min_lr=0.00001) were used to increase the success of the prediction models and to prevent over-fitting. After fine-tuning, the most appropriate hyperparameters and their values for the models were determined and presented in Table 2.

Table 1. Parameters and values used when fine-tuning the models

Fine-Tuning Parameters	**Fine-Tuning Models and Values**	
	GAF-AlexNet	**GAF-VGG16**
Fully Connected Layer Neurons Number	256, 512, 1024, 2048, 4096	256, 512
Dropout Value	0.1, 0.2, 0.3, 0.4, 0.5	0.1, 0.2, 0.3, 0.4, 0.5
Learning Rate (Using ReduceLROnPlateau)	0.00001 ~ 0.001	0.00001 ~ 0.001

Within the scope of the study, each model was run 10 times, and the best results were evaluated. Tables 3 and 4 present the evaluation results of the GAF-AlexNet and GAF-VGG16 models for the test sets, respectively.

Table 2. Hyperparameter values of the models used

Parameters	**Hyperparameter Values**	
	GAF-AlexNet	**GAF-VGG16**
Fully Connected Layer Density	2048-1024-2	256-256-2
Number of Training Rounds (Epoch)	50	50

Batch Size	32	32
Dilution (Dropout)	0.3 and 0.5	0.3
Activation Function	Relu	Relu
Optimization Algorithm	Adam	Adam
Learning Rate	0.001	0.001

Table 3. Performance metrics of GAF-AlexNet for test data

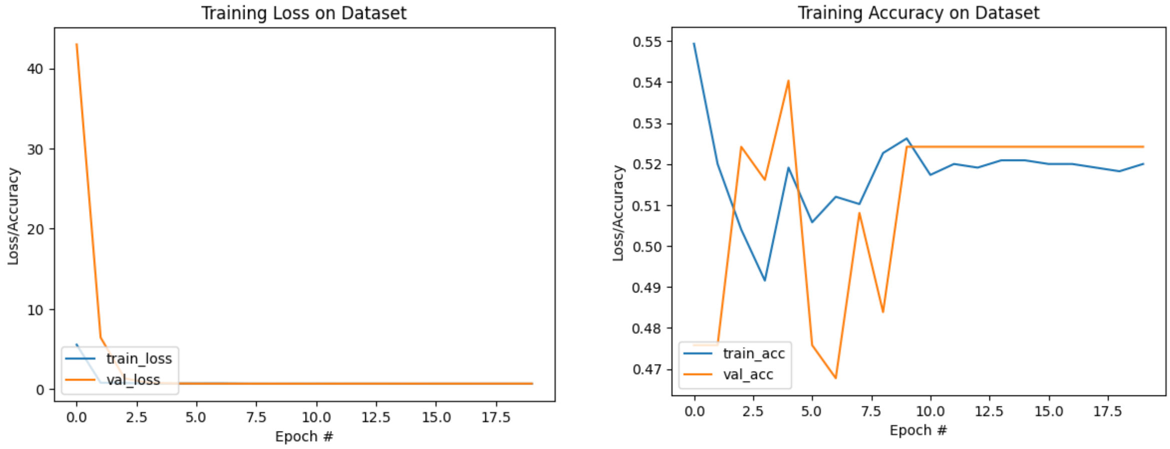
Performance Metrics	**Prediction Classes**	
	Down	**Up**
Precision	0.53	0.58
Recall	0.72	0.38
F1 Score	0.61	0.46
Accuracy	0.55	

Table 4. Performance metrics of GAF-VGG16 for test data

Performance Metrics	**Prediction Classes**	
	Down	**Up**
Precision	0.50	0.52
Recall	0.55	0.47
F1 Score	0.53	0.49
Accuracy	0.51	

GAF-AlexNet outperformed GAF-VGG16, which uses transfer learning. The main finding is that the GAF-AlexNet model achieves an accuracy of 55%. The training and validation loss plots of the proposed model are presented in Figure 7. Although these results seem very low for a deep learning model, compared to similar studies in the literature, the deep learning model achieves similar results. In fact, it is possible to integrate the forecast framework used into a trading strategy and achieve successful results. When trying to predict the direction of prices as "down" or "up", a forecast of just over 50% can be achieved, and substantial commercial success can be achieved. A good example of this is Barra et al. (2020) who showed that successful results can be obtained by integrating their models into the trading system, although the studies achieved an accuracy value of 56%.

Figure 7. Training and validation set accuracy/loss plots of the GAF-AlexNet model



4. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

The aim of this study is to predict oil price values by using oil exchange traded fund (ETF) data. Using a 5-day forecast window, the price trend of the next day was predicted. In this study, oil ETF data are represented as a 2D image using the Gramian angular field (GAF) method to benefit from the representation power of images, and then the AlexNet and VGG16 CNN architectures are used to analyze these image datasets. Several performance metrics were used to compare the performances of the proposed GAF-AlexNet and GAF-VGG16 models and existing models. The main finding is that the GAF-AlexNet model achieved an accuracy of 55%, making it applicable for decision support mechanisms. One of the key aspects that differentiates this study from other price prediction studies is the use of a novel input type that allows for converting image formats into time series, rather than relying on traditional numerical sequences. Thus, the study also presents a framework for new researchers to convert 1D time series into 2D-GAF images and demonstrates their applicability in advanced CNN architectures.

In future works, we plan to examine different 2D image transformations, develop a decision support system, and increase the accuracy by using new parameters and deep learning models.

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