Image-Based Cryptocurrency Trend Prediction with Explainable Deep Learning

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2024 9th International Conference on Information Technology Research (ICITR) | 979-8-3315-1142-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICITR64794.2024.10857799

***Abstract*—The rise of cryptocurrencies has reshaped financial markets, introducing assets that operate outside traditional banking systems. Yet, the market's volatility challenges traders who rely on manual technical analysis, which is both time-intensive and error-prone. This paper introduces CryptoVisionX, an advanced deep-learning framework designed for the automated prediction of cryptocurrency prices. Utilizing Convolutional Neural Networks (CNNs) for image feature extraction and Long Short-Term Memory (LSTM) networks for time series analysis, the model enhances prediction accuracy and efficiency. To combat data gaps, CryptoVisionX employs a comprehensive image-based dataset across various cryptocurrencies. Furthermore, it incorporates explainable AI (XAI) to increase the transparency of predictive models, fostering trust among users. The model's design navigates the trade-off between general applicability and precision, providing a scalable yet accurate forecasting tool. This research addresses key gaps in cryptocurrency analytics, offering a novel solution that could revolutionize trading strategies in the financial technology domain.**

***Index Terms*—Time Series Forecasting, Computer Vision, Explainable AI, Chart Analysis, Cryptocurrency Prediction**

I. Introduction

In recent years, the emergence of cryptocurrencies as a new class of digital assets has significantly changed the landscape of financial markets. With its decentralized nature, cryptocurrencies offer a novel approach to financial transactions, away from traditional banking systems. However, the cryptocurrency market is characterized by high volatility and unpredictability, presenting both opportunities and challenges for traders and investors [1]. The rapid fluctuations in cryptocurrency prices necessitate effective prediction tools to assist traders in making informed decisions.

Traditional methods of financial analysis, including fundamental and technical analysis, have been applied to cryptocurrency markets. Among these, technical analysis, particularly the study of chart patterns, has been widely used to predict price movements. However, this manual analysis of chart patterns is time-consuming, requires extensive expertise, and is subject to human error, leading to potential financial losses [2].

In response to these challenges, this study introduces CryptoVisionX, a novel approach to cryptocurrency price prediction that leverages deep learning techniques to automate the analysis of chart patterns. Combining CNNs for image-based feature extraction and LSTM networks for accurate time series forecasting, CryptoVisionX aims to enhance both the precision and efficiency of predictions. This hybrid model capitalizes on the strengths of CNNs in analyzing visual data and the capabilities of LSTMs in understanding temporal dependencies, providing a holistic solution for forecasting cryptocurrency prices [3]. To address the issue of data incompleteness and enhance model training [25], CryptoVisionX incorporates a novel, image-based dataset that includes a diverse array of cryptocurrency types.

Furthermore, acknowledging the importance of model transparency and interpretability in financial decision-making, this study integrates explainable AI techniques to demystify the predictive process of the model. The objective is to build a predictive model that not only achieves high accuracy but also gains the trust of its users by providing insights into its decision-making processes [4].

Current predictive models in the cryptocurrency domain often struggle with a trade-off between general applicability and specific accuracy. This study's hybrid model is designed to overcome this limitation by offering a flexible framework that can be adapted through specialized training for different cryptocurrencies, thereby maximizing both scalability and precision [26].

By systematically identifying and addressing these significant gaps, this research contributes to the existing body of knowledge and proposes practical solutions to enhance cryptocurrency trading strategies.

II. Background

Cryptocurrencies like Bitcoin and Ethereum have revolutionized financial transactions, offering a decentralized alternative to traditional systems. However, their high volatility makes accurate market predictions challenging, especially for traders who rely on manual chart analysis, which is prone to error and time-consuming. Traditional numerical prediction models, such as those using time-series data, often struggle to capture complex, non-linear relationships in cryptocurrency prices and require constant updates, reducing their efficiency in real-time trading environments.

Despite the widespread use of these methods, traders often struggle with the accurate analysis of complex chart patterns, leading to erroneous trading decisions. The accuracy of pattern recognition in technical analysis, which forms the core of many trading strategies, has been questioned due to the subjective interpretation of chart patterns and the significant time investment required to analyze them effectively [10]. These challenges underscore the need for more usable and automated analysis methods that can reduce human error and increase the efficiency of trading strategies.

The limitations of numerical dataset-based predictions in cryptocurrency markets are considerable. Such models often require regular updates with new data to remain effective, which can be cumbersome and resource-intensive. Additionally, these models typically lack adaptability across different time zones and cryptocurrencies, constraining their effectiveness to the specific conditions and datasets for which they were originally trained [13]. The need for continual data input and the inability to swiftly adapt to market changes or different cryptocurrencies diminish the practical usability of such applications, making them less reliable for traders who operate in a highly dynamic and global market [14].

The existing research on cryptocurrency price prediction has primarily focused on numerical datasets and traditional machine learning techniques, which, while groundbreaking initially, present several limitations. A key gap that this project seeks to address is the underutilization of image-based data for cryptocurrency forecasting, which can complement existing numerical approaches.

Numerous studies have employed time-series analysis for cryptocurrency price forecasting. For instance, methods like ARIMA and LSTM have been extensively used to predict price movements based on historical data [11]. However, these models are heavily dependent on large, continuously updated datasets, limiting their adaptability to sudden market shifts. In cryptocurrency markets, where volatility is the norm, models that rely solely on historical numerical data often fail to capture rapid changes [15].

Moreover, machine learning techniques such as Support Vector Machines (SVM) and Neural Networks have been explored for identifying non-linear patterns in price data. Despite their potential, these methods are often difficult to interpret and require substantial preprocessing, limiting their usability for real-time trading decisions. Traditional time series models like ARIMA and its variants are also insufficient for capturing the non-linear dynamics of cryptocurrency prices, as noted by [16].

While most research focuses on numerical data, there has been emerging interest in visual data for financial forecasting. For instance, [14] explored the conversion of time-series data into image formats, using CNNs to predict stock prices. This approach, though innovative, remains secondary in many studies, which still prioritize numerical analysis.

Several challenges persist in the current path of cryptocurrency forecasting, including:

1) **Data Dependency**: Most models require large, historical datasets, limiting their real-time effectiveness.
2) **Complexity and Usability**: Advanced models demand technical expertise, reducing accessibility for day-to-day traders [18].
3) **Lack of Adaptability**: Many models struggle to generalize across different cryptocurrencies and time zones, limiting their applicability for global traders.

Another significant limitation in the field is the lack of model interpretability, often making AI systems "black boxes." Predictive models offer limited insight into their decision-making processes. While these models can achieve high accuracy, users are left without explanations for their predictions, impacting trust and usability [19]. Coupled with XAI, this research not only improves accuracy but also enhances transparency and usability for traders, making AI predictions more interpretable and actionable.

In contrast, the application of image-based pattern recognition offers a more flexible and user-friendly approach. By analyzing visual data from chart images, these models allow traders to simply take a snapshot of a current chart pattern and submit it to the application for analysis and prediction. This method is inherently adaptable to any cryptocurrency and any time frame, significantly enhancing the usability and versatility of the predictive tools.

This image-based approach in the research simplifies the process of data entry and improves the transparency and interpretability of the predictions. Traders can see the exact patterns being analyzed, which aligns with how many traders visually assess charts, thus increasing the trustworthiness and acceptance of AI-driven predictive models in the trading community. The enhanced interpretability and ease of use provided by image-based models address significant barriers to AI adoption in cryptocurrency trading, offering an overall solution that aligns closely with trader workflows and preferences.

III. Proposed Solution

The proposed solution in this research is to develop a novel model application that combines computer vision, time series forecasting, and explainable AI techniques to forecast and interpret future cryptocurrency price patterns based on images of trading charts. This application addresses the limitations of traditional numerical data-based prediction models by using a visual approach that is more intuitive and user-friendly for traders.

The core of the proposed system involves three main components: a feature extraction module using the **ResNet50** pre-trained CNN model, **LSTM** a type of Recurrent neural network for time series forecasting, and **Grad-Cam** an XAI technique for model interpretability.

1) The system uses the chart image dataset created by the author using online trading view platforms and is then processed using ResNet50, a powerful CNN model that has shown significant success in image classification tasks. ResNet50 is used to extract meaningful features from the chart images, capturing intricate patterns and

trends that may not be evident through numerical analysis alone [22].

2) After feature extraction, the identified features are fed into an LSTM model, which is adept at handling sequences and time series data. LSTM networks are particularly beneficial for this application due to their ability to remember important information over long sequences, making them ideal for predicting future market behaviors based on past trends [23].
3) To enhance the trust and usability of the application, the proposed solution uses Gradient-weighted Class Activation Mapping (Grad-CAM) heatmaps to provide visual explanations of the predictions. Grad-CAM uses the gradients of any target concept flowing into the final convolutional layer to produce a coarse localization map highlighting important regions in the image that contribute most to the target concept. This method makes it possible to understand which parts of the initial chart were most influential in the prediction, thereby offering users insights into the model's decision-making process [24].

The proposed application represents a significant advancement in cryptocurrency prediction technologies. By integrating a novel combined model with the use of visual factors, the system offers a powerful tool that forecasts future price movements and provides users with understandable insights into the prediction processes.

IV. System Architecture

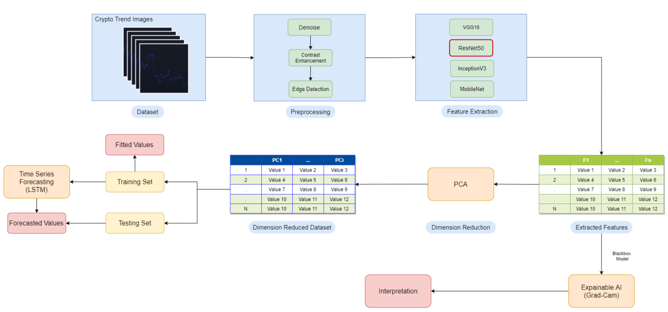

Fig. 1. High-level architecture of the system model

The architecture of the proposed solution, CryptoVisionX, consists of a sequential flow of processes designed to transform input cryptocurrency trend images into predictive output with explainable features as shown above.

A. Dataset Preparation

The dataset preparation is done by capturing chart images set to a 4-hour chart format, representing monthly time frame patterns across multiple cryptocurrency pairs such as BTCUSDT and ETHUSDT. The images are systematically organized based on the month and type of cryptocurrency, ensuring that the dataset encompasses a diverse range of market conditions and trends. This structured organization allows the model to analyze and predict future price movements by recognizing these visual patterns within the cryptocurrency charts. For each chart, the features extracted are sequentially organized based on month, representing a timeline of price movements for the past years. This sequential structure allows the LSTM to recognize temporal dependencies and predict future trends. Ground-truth labels are generated by shifting the target variable, where the next period's price movement (such as the price at the next 1-month interval) is used as the ground truth. The features used include chart pattern details like price movements, support and resistance levels, and trend directions, ensuring that both historical and current data inform the LSTM's predictions.

B. Preprocessing

Once the dataset is prepared, each image undergoes a series of preprocessing steps to enhance its quality and ensure it is suitable for feature extraction:

1) Denoising: To remove any extraneous noise that could affect the model's accuracy.
2) Contrast Enhancement: To make the patterns more distinct and recognizable for the feature extraction phase.
3) Edge Detection: To outline the most important features in the image, such as trend lines and pattern boundaries, facilitating more precise feature extraction.

C. Feature Extraction

Following preprocessing, the images undergo feature extraction using ResNet50, a deep Convolutional Neural Network known for capturing complex visual patterns. In this implementation, the final classification layer of the model is removed, and a Global Average Pooling (GAP) layer is added to adapt the model for feature extraction. This modification allows the model to distil essential information from the charts by capturing visual cues and underlying patterns that indicate future price movements. These extracted features are then used in the subsequent time series forecasting phase.

D. Dimension Reduction

The high-dimensional data extracted by ResNet50 is then subjected to dimensionality reduction using Principal Component Analysis (PCA). It reduces the feature space to the components that capture the most variance in the data, which simplifies the model without significant loss of information. This reduced dataset retains the most critical features needed for accurate forecasting and plotting.

E. Time Series Forecasting

Once the essential features are extracted and the dimensionality is reduced, the model proceeds to the time series forecasting phase. Here, the LSTM network is employed due to its capability to manage sequential data and temporal dependencies. LSTM is well-suited for this task as it can retain information over time, making it effective for predicting future cryptocurrency price trends based on the sequential data provided from chart patterns. The extracted features serve as inputs to the LSTM network, which then forecasts upcoming market movements by learning from the historical price trends captured in the charts.

F. Model Interpretation

Finally, to ensure transparency and trust in the model's predictions, Grad-CAM heatmaps are used providing visual explanations for the predictions. By highlighting the areas of the input image that most significantly influenced the model's output, Grad-CAM demystifies the black box nature of the LSTM, allowing users to understand the reasoning behind the predictive patterns.

G. Output

The result is a forecasted value represented as a predicted price pattern, which is directly usable by traders. This pattern not only predicts the future trend but also aligns with the user's understanding of market behaviors, thereby enhancing the decision-making process in cryptocurrency trading.

V. Algorithm Design

The design of the CryptoVisionX model algorithm is a complex, multi-stage process involving the following key phases.

A. Feature Extraction Using ResNet50

During the feature extraction stage, the system uses a modified CNN, originally based on a classification model, to analyze chart images of cryptocurrency markets. A notable adaptation in this model is the replacement of the original final classification layer with a Global Average Pooling 2D layer. This adjustment aids in distilling the most salient features from the preprocessed images. The output from this phase is a set of high-dimensional feature vectors that encapsulate the distinctive trends and elements present in the cryptocurrency market charts.

B. Time Series Forecasting Using LSTM

In this research, the LSTM model is used for time series forecasting, specifically leveraging sequential data extracted from chart images.

- Sequential model architecture: The foundation for the LSTM network is a sequential architecture, allowing for step-by-step processing of input data. Unlike traditional numeric-based predictions, the model uses features extracted from chart images that are sequentially organized based on time, capturing the flow of price movements over intervals. Each sequence of extracted features represents a timeline of cryptocurrency price fluctuations.
- **Feature-to-sequence transformation:** To adapt image-based features for LSTM's sequential data processing, multiple chart images (spanning different time frames, such as 4-hour intervals over a month) are used. The visual data from these images is converted into sequential input where each timestep represents one chart snapshot. This structure mirrors the inherent temporal relationships in price data and allows LSTM to model temporal dependencies effectively.
- **LSTM layer with 100 units:** The network incorporates a layer with 100 LSTM units, chosen to capture long-term dependencies in the time series. The **ReLU activation function** is used to enable the learning of complex, non-linear relationships within the data, improving the model's ability to predict future price trends.
- **Dense layer for output:** After LSTM processing, a dense layer is integrated to generate the predicted output. The number of neurons in this layer corresponds to the features produced by the PCA during dimensionality reduction, ensuring that the model can produce accurate predictions based on the reduced feature set.
- **Model training and optimization:** The model is compiled using the **Adam optimizer**, a widely used optimization algorithm that adapts the learning rate during training, ensuring stable and efficient learning. The LSTM is trained on sequences of image-extracted features, with the network learning to predict future price trends by adjusting its weights based on the difference between predicted and actual outcomes over time.
  While traditional numerical data can capture trends, image-based features offer a visual dimension that reflects patterns traders often rely on, such as chart formations. These visual patterns are better represented through CNN-based image feature extraction, and when combined with LSTM, they enable the model to capture both visual and temporal trends, providing a more comprehensive prediction system.

By transforming image-based chart patterns into sequences, the model capitalizes on the strengths of both CNNs and LSTM networks, providing a novel approach that bridges the gap between visual pattern recognition and sequential time series forecasting.

C. Explainable AI Using Grad-CAM

- **Feature Maps Generation:** The algorithm passes the input image through the CNN up to the final convolutional layer, generating feature maps that capture crucial visual patterns associated with the target prediction.
- **Gradient Computation:** It computes the gradient of the output layer's target class with respect to the last convolutional layer's feature maps, indicating the significance of each map.
- **Gradient Pooling:** Global average pooling is performed on these gradients across the feature maps, deriving a singular, impactful value for each map.
- **Feature Maps Weighting:** Subsequently, each feature map is weighted according to the pooled gradients, highlighting the contribution of each map to the target prediction.
- **Heatmap Synthesis:** The weighted feature maps are aggregated to form a 2D heatmap that underscores the regions instrumental in predicting the target class.
- **Heatmap Normalization:** The heatmap is normalized to a 0-1 scale for enhanced visualization and interpretation.

- **Overlay Visualization:** The algorithm overlays the heatmap onto the original input image to clearly delineate the areas most relevant to the predicted price movement.

VI. Evaluation and Conclusion

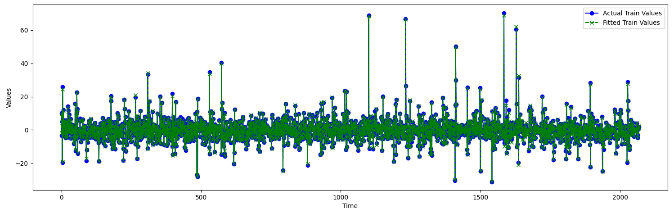

Fig. 2. Plot of actual train and fitted values

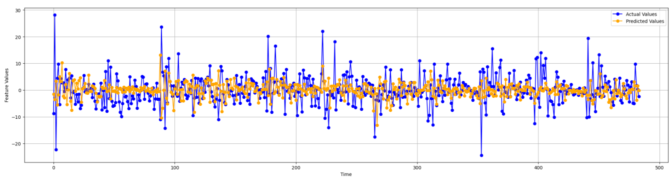

Fig. 3. Plot of actual test and forecasted values

The evaluation of the CryptoVisionX model centers on an in-depth analysis of the predictive performance using visualizations of fitted and forecasted values against actual data. The first plot, detailing 'Fitted Values and Actual Training Data,' demonstrates the model's proficiency in capturing the underlying trend within the training data. Despite the presence of outliers attributed to the volatile nature of cryptocurrency markets—the model exhibits a consistent pattern, closely mirroring the actual values with a high degree of fidelity.

Moving to the second plot, 'Forecasted Values and Actual Test Data,' the model's robustness is further underscored. It showcases the forecasted values in comparison with the actual test data, reflecting the model's capacity to generalize from the training and accurately predict future trends. Although there are variances between the forecasted and actual values, which is expected in the domain of financial markets, the model maintains a commendable predictive trajectory.

The results derived from the test sets suggest that the CryptoVisionX model performs with remarkable effectiveness. This research has taken a pioneering step in involving image-based data for cryptocurrency price pattern prediction, innovating beyond the conventional reliance on numerical data. By doing so, it has crafted an application that stands as a testament to the feasibility and utility of image-based approaches in the field of financial forecasting.

ResNet50 model outperforms other pre-trained models like VGG16, InceptionV3, and MobileNet models when used for feature extraction in conjunction with an LSTM for time series forecasting based on the evaluated metrics.

The ResNet50 model also offers clearer and more focused Grad-CAM visual explanations across the various patterns tested compared to the other architectures, VGG16 and InceptionV3. The heatmaps produced by ResNet50 show precise areas of interest, indicating that this model is better at pinpointing relevant features in the chart images.

TABLE I

: LSTM models' performance based on extraction model

Extraction Model	No. Of PCs	Loss	MSE	MAE
ResNet50	44	15.9558	15.955791	2.5862
VGG16	44	44.9034	44.903393	4.8198
InceptionV3	34	52.4555	52.45551	4.8445
MobileNet	50	23.0880	23.08801	3.3723

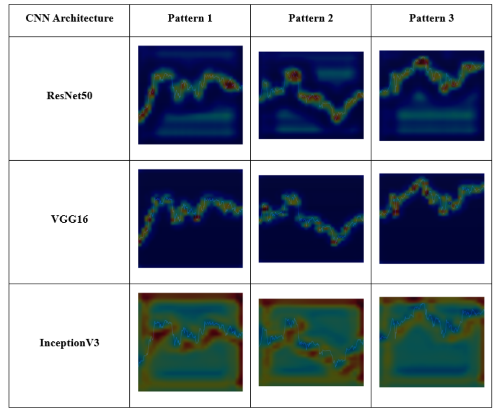

Fig. 4. Grad-Cam Interpretation results based on Feature Extraction Model

The utilization of techniques such as ResNet50 and LSTM, coupled with Grad-CAM enhances prediction accuracy and also instills a layer of interpretability often missing from similar applications.

VII. Limitations and Future Work

While the current implementation of CryptoVisionX demonstrates the efficacy of integrating image-based data with LSTM for cryptocurrency forecasting, several limitations and challenges remain.

One primary limitation is that Grad-CAM explanations are only applied to the CNN outputs and do not extend to the predictions generated by the LSTM. This presents a gap in the model's interpretability, as the sequential decision-making process in LSTM remains a "black box." Expanding explainability methods to LSTM predictions could provide a more comprehensive understanding of the forecasting mechanism. Additionally, image-based predictions bring inherent challenges, such as their susceptibility to adversarial attacks—small perturbations in images can significantly alter the model's predictions. This vulnerability poses risks, especially in highly volatile markets like cryptocurrency. Another challenge lies in adapting the model to varied time-step spacings and different chart presentations, as the lack of a standardized chart format complicates the prediction process, potentially reducing the model's generalizability across various charting styles and time frames.

Furthermore, the model's predictions are currently limited to visual chart patterns and do not incorporate numerical price values or account for external factors like market sentiment, news, or broader economic trends. This limits the model's capability to provide holistic trading strategies that factor in the complexities of real-world cryptocurrency markets.

Future work will address these challenges by expanding the model's adaptability and predictive accuracy. Planned enhancements include:

- **Web scraping APIs** to collect real-time chart data.
- Integration of external data sources such as **social media sentiment analysis** and **news analytics**, broadening the scope of factors that influence market trends.
- Improving model robustness against **adversarial attacks** and increasing flexibility for varying **time-step intervals** and **chart formats**.
- Exploring **explainability techniques** beyond Grad-CAM, particularly for **LSTM predictions**, to provide transparent and interpretable forecasts for end users.

By tackling these limitations, the model aims to offer a more reliable, adaptable, and user-friendly solution for cryptocurrency traders navigating the dynamic market landscape.

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