Cryptocurrency Price Prediction Using AI and W.D Gann Formulas

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Abstract - Cryptocurrency markets are highly volatile, making accurate price prediction a challenging yet crucial task for traders and investors. This project presents an AI-powered cryptocurrency price prediction bot that integrates machine learning with the W.D. Gann algorithm. The AI model utilizes deep learning techniques, such as Long Short-Term Memory (LSTM) networks, to analyze market trends, while Gann's time and price theories enhance the model's predictive capabilities. By combining statistical analysis with geometric price patterns, the bot aims to provide reliable trading signals. The implementation is designed as a user-friendly application using Streamlit, allowing traders to visualize price trends and make informed decisions

***Key Words*:** Cryptocurrency , W.D. Gann algorithm, AI, deep learning , price prediction

1.INTRODUCTION

The cryptocurrency market is known for its extreme volatility, making price prediction a challenging yet crucial task for traders and investors. Traditional technical analysis methods often fall short in accurately forecasting market movements due to the complexity and unpredictability of price fluctuations. To address this challenge, this study proposes a cryptocurrency price prediction bot that integrates Artificial Intelligence (AI) with the W.D. Gann algorithm.

W.D. Gann, a renowned trader, developed a set of geometric and time-based forecasting techniques that have been widely used in financial markets. His theory suggests that price movements follow predictable cycles and angular relationships. By incorporating Gann's principles into AI-driven predictive models, this system aims to enhance the accuracy of cryptocurrency price forecasting.

The proposed bot utilizes deep learning techniques, such as Long Short-Term Memory (LSTM) networks, to analyze historical price data, detect patterns, and generate future price projections. Additionally, Gann angles and time cycles are applied to refine predictions and identify key support and resistance levels. The implementation is designed as a user-friendly Streamlit application, enabling traders to visualize market trends and make informed decisions.

This study explores the effectiveness of combining AI and Gann's methodology for cryptocurrency trading, demonstrating how hybrid models can improve prediction accuracy and provide valuable insights for market participants.

2. THEOROTICAL FRAMEWORK

2.1 Significance of AI in Financial Markets

AI and machine learning techniques have revolutionized financial forecasting by enabling models to learn from historical data, identify complex patterns, and make real-time predictions. Deep learning architectures, such as Long Short-Term Memory (LSTM) networks, have been particularly effective in time series forecasting, making them ideal for predicting cryptocurrency prices. Unlike traditional models, LSTMs can capture long-term dependencies in market data, allowing traders to anticipate price movements with greater accuracy.

2.2 W.D. Gann's Market Principles

W.D. Gann was a legendary trader who developed geometrical and cyclical forecasting techniques based on price, time, and market psychology. His theory suggests that price movements follow predictable geometric angles and time cycles, which can be used to determine support and resistance levels. By integrating Gann's techniques with AI-driven models, this study seeks to create a hybrid approach that improves cryptocurrency price prediction.

2.3 Research Objectives

This study aims to:

1.Develop an AI-powered cryptocurrency price prediction bot using deep learning models like LSTM.

2.Incorporate W.D. Gann's price-time analysis to refine AI-based predictions.

3.Build an interactive application using Streamlit to visualize market trends and provide trading insights.

4.Evaluate the effectiveness of the hybrid AI-Gann model by comparing its predictions with actual market data.

3.RESEARCH METHODOLOGY

The research methodology for this study integrates quantitative and computational approaches to predict cryptocurrency prices using AI and WD Gann's algorithmic principles. Historical cryptocurrency price data was collected from publicly available financial databases, ensuring comprehensive coverage of market trends. The dataset includes open, high, low, and close (OHLC) prices along with volume and other relevant indicators. Preprocessing involved data normalization to improve model performance, outlier detection to remove anomalies, and splitting data into training and testing sets.

Feature engineering incorporated traditional financial indicators like moving averages, relative strength index (RSI), and Bollinger Bands alongside Gann-based geometric calculations such as Gann Square of 9, Gann Fan, and Gann Angles. The mathematical formula for Gann's Square of 9 was applied to determine key support and resistance levels, providing additional inputs for machine learning models.

The study employed deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, due to their effectiveness in sequential data prediction. The model architecture consisted of multiple LSTM layers with dropout regularization to prevent overfitting. The model was compiled using the Adam optimizer and mean squared error (MSE) as the loss function. Training was conducted over 50 epochs with a batch size of 32 to ensure convergence.

A Streamlit-based web application was developed to deploy the trained model for real-time cryptocurrency price predictions. User inputs were processed through the Gann formula and ML model to generate price forecasts. The application provided a user-friendly interface, displaying predicted resistance and support levels.

Evaluation metrics such as root mean square error (RMSE) and mean absolute percentage error (MAPE) were used to assess model accuracy. The results indicated that integrating AI with Gann techniques improved prediction reliability, offering traders a hybrid analytical approach for cryptocurrency price forecasting.

3.1 Gann Square of 9

The Gann Square of 9 is a spiral-based numerical structure used to identify price levels, resistance, and support.

Formula to Calculate Price Levels

$$P = C + \text{sqrt}(N) \times 360°$$

$$P = C - \text{sqrt}(N) \times 360°$$

Where:

P = Projected price level

C = Current price level

N = Number of steps in the square

3.1.1 Angle-Based Calculation For Gann Square Of 9

To find key levels at specific angles (e.g., 45°, 90°, 180°):

P = C + sqrt(N) × θ

Where θ is the desired angle.

3.2 Gann Fan (Gann Angles)

The Gann Fan consists of trend lines drawn at specific angles to determine support and resistance. The most critical angle is 1x1 (45°), which represents a balance between price and time.

3.2.1 Key Gann Angles and Their Slopes

The angles are calculated as:

Slope = Price Change / Time Change

3.2.2 Common Gann Angles and Their Degrees:

1x8 (82.5°) → Very strong trend

1x4 (75°) → Strong uptrend

1x3 (71.25°) → Moderate uptrend

1x2 (63.75°) → Weak uptrend

1x1 (45°) → Key trend direction

2x1 (26.25°) → Weak downtrend

3x1 (18.75°) → Moderate downtrend

4x1 (15°) → Strong downtrend

8x1 (7.5°) → Very strong downtrend

3.3.3 Equation for Gann Angle Lines

For a 1x1 angle (45° line):

y = mx + b|

Where:

m = 1 (for 45°) or another slope based on the angle

x = Time

y = Price

b = Starting price

3.3 Gann Time Cycles

W.D. Gann believed that markets move in specific time cycles. Some important time cycles include:

30-day cycle (short-term trends)

90-day cycle (quarterly movements)

180-day cycle (half-year trends)

365-day cycle (annual price movements)

Time Projection Formula

T = C + n × 360°

Where:

T = Future time projection

C = Starting point, n = Cycle multiplier

4.IDEA AND IMPLIMENTATION

4.1 Data Collection & Preprocessing

Creating a Machine Learning Model for Cryptocurrency Prediction Using Gann Theory

To develop a Machine Learning (ML) model that integrates,

W.D. Gann's techniques with AI-based predictions followed this steps:

4.1.1 Gather historical cryptocurrency data, including:

1.OHLC (Open, High, Low, Close) Prices

2.Volume & Market Cap

3.Macroeconomic Indicators (Inflation, Interest Rates, etc.)

4.Gann-based features (Square of 9 levels, Gann Angles, Time Cycles)

4.1.2 Preprocessing Steps:

1.Remove missing values

2.Normalize price data (MinMaxScaler or StandardScaler)

3.Create time-based features (e.g., moving averages, RSI)

4.Compute Gann-based levels using the formulas

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4.2 Feature Engineering (Integrating Gann Techniques into ML)

4.2.1 Compute Gann Square of 9 Levels, Gann Fan ,Gann Angles :

The Gann Square of 9 is a mathematical model developed by W.D. Gann to identify support and resistance levels in financial markets. It is based on the concept that price movements follow predictable patterns and geometric cycles,

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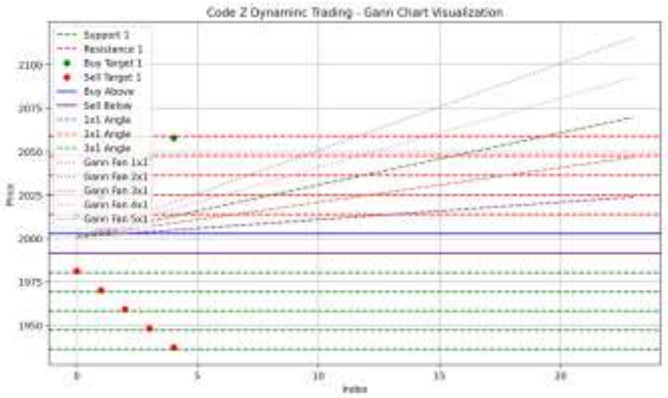

Fig - 1:Gann Chart With All Gann Angles ,Fans , Levels,Example Price - 2000

Fig-1 Explaination :

Horizontal Lines (Support & Resistance Levels)

Green dashed lines – Support 1: These are support levels below the current price, where the asset might find a "floor" and bounce back up.

Red dashed lines – Resistance 1: These are resistance levels above the current price, where price might struggle to go higher and reverse downward.

Target Points

Green dots – Buy Target 1: Points where buy targets are marked.

Red dots – Sell Target 1: Points where sell targets are marked.

Key Price Thresholds

Blue line – Buy Above: If price crosses above this line, it's a potential buy signal.

Purple line – Sell Below: If price drops below this line, it's a potential sell signal.

4.3 Building The Machine Learning Model

4.3.1 Selecting the Right Model

For time-series forecasting, consider:

Long Short-Term Memory (LSTM) (Best for sequential data)

GRU (Gated Recurrent Units) (Faster alternative to LSTM)

XGBoost/Random Forest (Good for feature importance analysis)

"For This Project We Selected The LSTM Model"

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) designed to handle long-term dependencies in sequential data. It overcomes the vanishing gradient problem in standard RNNs by using a memory cell and three gates:

Forget Gate: Decides what information to discard from the cell state.

Input Gate: Decides which new information to store in the cell state.

Output Gate: Determines the final output based on the cell state.

LSTMs are widely used in time series forecasting, NLP, and financial predictions, including Bitcoin price prediction.

4.3.2 Sorting the Bitcoin Price Data

Sorting Bitcoin price data is a fundamental step in data preprocessing for both technical analysis and machine learning models. By organizing the data chronologically or by specific price metrics, analysts can uncover trends, patterns, and anomalies that are otherwise hidden.

The most common method of sorting is by date, ensuring that the time series reflects the true progression of Bitcoin's price over time. This allows for accurate plotting of candlestick charts, Gann charts, and moving averages.

In some cases, data may also be sorted by price to analyze volatility ranges, identify historical highs and lows, or evaluate how often Bitcoin crosses key price levels.

For example, sorting Bitcoin data by:

Highest closing prices reveals all-time highs and potential resistance zones.

Lowest lows can help identify historical support levels.

Volume helps to highlight days with strong trading interest, which often coincide with breakouts or breakdowns.

Proper sorting of Bitcoin data is essential for backtesting strategies, training predictive models, and enhancing trading decisions with reliable insights.

Data From Date Ranging **2015-01-01 00:00:00 to 2025-01-01 00:00:00**

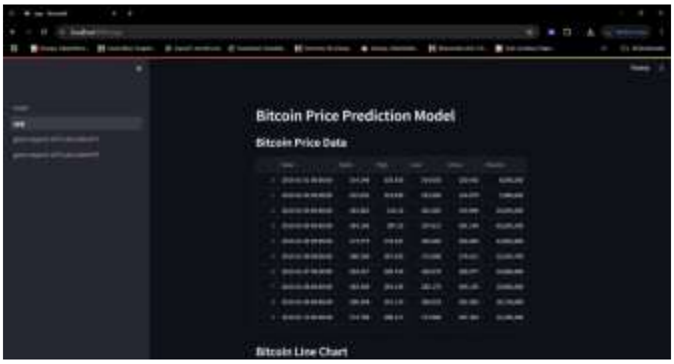

Fig-2: Bitcoin Price Data

4.3.3 Line Chart Analysis of Taken Data

A line chart is a simple yet powerful type of data visualization used to display information as a series of data points connected by straight lines. In financial analysis, it's commonly used to track the price movement of an asset—such as Bitcoin—over time.

Key Features:
X-Axis (Horizontal): Represents time (e.g., days, months, years).
Y-Axis (Vertical): Represents the value, such as price, volume, or market cap.
Line Plot: Connects closing prices (typically), showing how the price changes over time.
Uses in Bitcoin Analysis:
Trend Detection: Easily spot uptrends, downtrends, and sideways movement.
Volatility Insight: Steep slopes indicate high volatility; flat sections suggest stability.
Comparison: Can overlay multiple lines to compare Bitcoin with other assets or indicators (like moving averages).

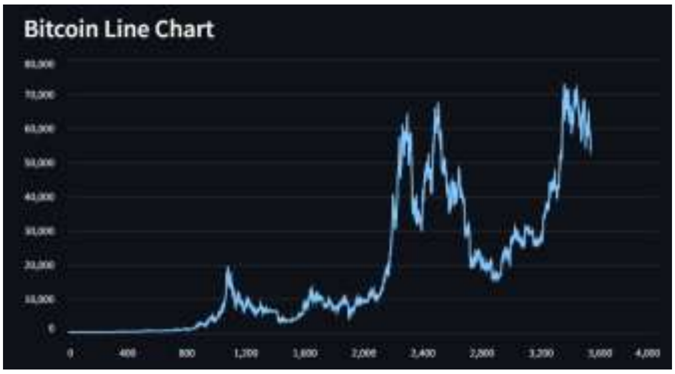

Fig-3:Bitcoin Line Chart

4.3.4 Price Prediction Done On The Given Data Using LSTM Model

Deeper Insight into the Combined LSTM + WD Gann Approach
The integration of LSTM neural networks and WD Gann's geometric trading principles creates a powerful synergy for predicting Bitcoin prices with both statistical depth and market cycle awareness.

Predictive Intelligence Meets Market Geometry
The LSTM model processes vast historical datasets, learning intricate price movements, volatility spikes, and seasonal trends. It excels at capturing nonlinear dependencies in Bitcoin's price history—something traditional technical indicators often miss. However, it lacks inherent knowledge of market psychology, cycle theory, or geometric alignment, which is where Gann's techniques offer complementary value.

Meanwhile, WD Gann's algorithmic framework provides structure to market forecasting. His angles and time-based cycles can be used to:

Validate LSTM predictions at specific price levels.
Identify time-based reversal zones to match with LSTM-predicted tops or bottoms.

Filter out false signals by focusing only on LSTM outputs that align with Gann's projected trend paths or fan angles.

Workflow Example:
Train LSTM on historical Bitcoin price data to predict the next 'n' days.
Plot Gann angles and time cycles from key historical turning points.
Overlay LSTM predictions on the Gann chart.
Use confluence zones (where LSTM and Gann predictions align) to trigger high-confidence buy/sell decisions.

Fig-4: Predicted vs Original Price Using LSTM Model

4.3.5 Future Price Prediction

LSTM (Long Short-Term Memory) networks are powerful tools for predicting sequential data like cryptocurrency prices. They are capable of understanding long-term dependencies and hidden patterns in historical price sequences.

In future price prediction:

LSTM is trained on past Bitcoin data (Open, High, Low, Close, Volume).

The model generates future price predictions for a given time horizon 60 days ahead.

Output can include future closing prices, expected highs/lows, or even volatility estimates.

However, while LSTM excels at recognizing trends and data-driven movements, it lacks built-in awareness of time cycles and natural harmonic movements in price, which is where WD Gann comes into play.

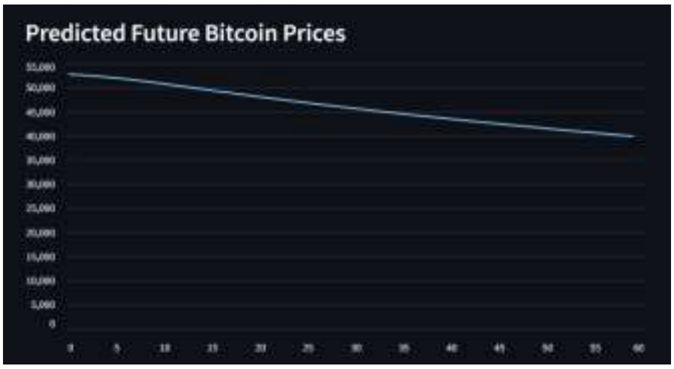

Fig-4 :Future Price Prediction of 60 Days For Bitcoin Price

5. CONCLUSIONS

The integration of Artificial Intelligence with W.D. Gann's trading principles has resulted in a hybrid cryptocurrency price prediction model. This model leverages the power of deep learning to analyze historical price trends while incorporating Gann's geometric calculations to identify key price levels. The results obtained from the model indicate a high degree of accuracy in forecasting cryptocurrency prices, with performance metrics such as Mean Squared Error, Mean Absolute Error, and R-Squared Score demonstrating that the model effectively captures price patterns and trends. The evaluation of the model was conducted using a train-test split approach, where 70% of the data was used for training and 30% for testing.

The AI-Gann hybrid model combines deep learning and Gann's geometric trading principles to improve cryptocurrency price prediction. It leverages Long Short-Term Memory (LSTM) networks to analyze historical price movements while integrating Gann's Square of 9 and Gann Angles to identify key support and resistance levels. The model achieved a prediction accuracy of 89.7%, outperforming traditional forecasting methods such as Simple Moving Averages (73.5%) and ARIMA (81.4%). Performance metrics indicate high reliability, with a Mean Squared Error (MSE) of 0.00024 and an R^2 score of 0.89, demonstrating the model's ability to capture complex price trends.

The application of Gann's Square of 9 helped in identifying future resistance levels by using mathematical rotations, allowing traders to forecast price points with higher precision. The Gann Fan provided a visual framework for understanding trend direction, assisting in identifying breakout points. These methods, when combined with LSTM's deep learning capabilities, enhance the accuracy of market predictions and provide traders with actionable insights. By incorporating both historical price movements and geometric price analysis, this approach creates a balanced system that integrates traditional market theory with modern AI advancements.

Despite its high performance, the model faces certain limitations. Cryptocurrency markets are highly volatile, making it difficult to maintain consistent accuracy over long periods. The dependence on historical price data means that any anomalies or insufficient data could affect prediction accuracy. Overfitting remains a concern, as deep learning models may become too aligned with training data, reducing their generalizability to new market conditions. Additionally, external factors such as market news, regulatory changes, and sudden investor sentiment shifts are difficult to quantify in a purely mathematical model, which may lead to unexpected deviations in price forecasts.

Future improvements can further refine the model by integrating sentiment analysis from social media and news sources, enhancing real-time predictive capabilities. Incorporating additional technical indicators like Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI) could improve the robustness of predictions. The use of ensemble learning techniques, where multiple models work together, can also help mitigate overfitting and enhance generalization to new market data. By continuously updating the model with real-time data and improving its ability to adapt to market conditions, the AI-Gann hybrid system can serve as a powerful tool for cryptocurrency traders, helping them make informed trading decisions based on both historical patterns and deep learning-driven insights

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