**ASSETS PRICE PREDICTOR**

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**Abstract:**

The intricate nature of asset price data, influenced by multifaceted conditions, has posed significant challenges for Artificial Intelligence (AI) and Machine Learning (ML) applications. Recent studies emphasize the complexity of relying solely on a single learning model for accurate predictions. This complexity is further amplified for companies within the construction sector, where the behavior of assets is intricately tied to a multitude of conditions. This study addresses these challenges by presenting a hybrid model designed to enhance prediction accuracy for the price index of assets within the construction sector. The key contributions of this research are twofold: Firstly, an ensemble model incorporating Artificial Neural Network (ANN), Gaussian Process Regression (GPR), and Classification and Regression Tree (CART) is introduced. This ensemble approach leverages the strengths of each prediction model to compensate for individual errors. Secondly, an optimization technique is employed to assess the impact of each learning model on prediction outcomes. The algorithms simultaneously process data and conduct prediction operations. Subsequently, the Cuckoo Search (CS) algorithm determines optimal coefficients, representing the weight of each algorithm's contribution. Through an ensemble technique, the results are combined, yielding a final output through weighted averaging based on these optimal coefficients.

**Objective:**

Our primary goal is to develop a robust machine learning model capable of forecasting [asset] prices with precision and reliability.

Rationale:

Financial markets are inherently volatile, shaped by numerous factors and intricate patterns. Accurate predictions empower investors, traders, and financial analysts to make informed decisions, mitigating risks and maximizing opportunities.

Significance:

Inaccurate predictions can lead to substantial financial losses, emphasizing the need for advanced tools and methodologies. Our project addresses this need by harnessing the power of machine learning to enhance predictive capabilities.

**Approach:**

Data Preparation: Preprocess financial asset data, handle missing values, scale numerical features, and encode categorical variables using label encoding techniques.

Label Encoding Implementation: Apply label encoding to convert categorical variables into numerical format suitable for machine learning model ingestion.

Model Training: Utilize encoded data to train machine learning models (e.g., regression, random forest) for asset price prediction.

Performance Evaluation: Assess model performance using metrics like MAE or RMSE to gauge predictive accuracy.

Refine Label Encoding: Continuously refine label encoding strategies, exploring alternative techniques or feature engineering to improve model accuracy.

Model Fine-Tuning: Optimize models by adjusting hyperparameters and configurations to enhance accuracy in forecasting asset prices.

Validation and Iteration: Validate model performance on separate test datasets and iterate for further improvements.

**DATA COLLECTION:**

THERE CAN BE DIFFERENT DATA SOURCES WHICH CAN HELP US TO PREDICT THE FUTURE PRICE OF AN ASSET SOME OF THEM ARE LISTED BELOW AND EXPLAINED FURTHER :

HISTORICAL PRICE DATA

MARKET INDICATORS

RELEVANT FACTORS

PATTERNS

**HISTORICAL PRICE DATA:**

**Pattern Recognition:**

* Chart patterns, such as head and shoulders, triangles, and double tops/bottoms, are based on historical price movements. Traders use these patterns to anticipate potential future price reversals or continuations.

**Statistical Models and Machine Learning:**

* Sophisticated statistical models and machine learning algorithms can analyze historical price data to identify patterns and relationships that may be predictive of future price movements.

These models may consider a wide range of features and factors beyond simple price trends.

**Investor Psychology:**

* Historical price data contributes to investor psychology. Traders and investors often make decisions based on past experiences and reactions to market events, influencing the supply and demand dynamics that, in turn, affect future prices.

**Trend Analysis:**

* Historical price data is commonly used to identify trends in asset prices. Trends, whether upward, downward, or sideways, can offer indications of the asset's momentum and the potential direction of future prices

**MARKET INDICATORS:**

Market indicators predict stock future prices by analyzing trends, momentum, volatility, volume, and sentiment. Moving averages and trend lines identify the direction of price movement, while indicators like RSI and MACD gauge momentum. Volatility indicators such as Bollinger Bands and ATR highlight potential price swings. Volume indicators like OBV and Volume Profile assess buying and selling pressure. Sentiment indicators, including the put/call ratio and VIX, offer insights into market sentiment. Economic indicators such as interest rates and economic reports influence broader market conditions. Traders use a combination of these indicators to make informed predictions, considering external factors that may impact stock prices.

**NEWS AND FACTORS:**

News and events exert significant influence on real estate and stock prices. In the stock market, positive news like strong earnings reports, product launches, or favorable economic indicators often leads to increased investor confidence and higher stock prices. Conversely, negative news such as economic downturns, geopolitical tensions, or corporate scandals can result in stock selloffs. In real estate, news of economic growth, favorable interest rates, or urban development projects can boost property values. Adversely, negative news such as housing market crises, regulatory changes, or economic recessions can contribute to declining real estate prices as investor confidence wanes

**CONTRIBUTION:**

Implemented Random Forest algorithm for predicting Dogecoin prices, leveraging historical market data and tailored features.

Applied label encoding techniques to facilitate Diamond price prediction using machine learning models, enhancing categorical variable representation.

Employed Linear Regression models in Real Estate valuation, utilizing property features for accurate price forecasting within the housing market.

Using ARIMA as a baseline provides a fundamental understanding of Bitcoin price trends and seasonality, allowing for comparisons with more complex models and assisting in the refinement of predictive techniques for Bitcoin price forecasting.

**ALGORITHM:**

ARIMA MODEL(BITCOIN PRICE PREDICTOR)

The ARIMA (AutoRegressive Integrated Moving Average) model is a time-series forecasting method designed to capture and predict temporal patterns in data. It combines autoregressive (AR) elements, which model the dependency on past values, with differencing (I) to make the time series stationary, and moving average (MA) components that consider past forecast errors. The model is characterized by three parameters: p (AR order), d (degree of differencing), and q (MA order). ARIMA is effective for handling non-stationary time series data, making it widely used in finance, economics, and various fields for predicting future values based on historical patterns and trends.

LINEAR REGRESSION(REAL ESTATE)

Linear regression is a statistical method used for modeling the relationship between a dependent variable and one or more independent variables. The model assumes a linear connection, expressing the dependent variable as a linear combination of the independent variables, each weighted by coefficients. The goal is to find the best-fitting line that minimizes the sum of squared differences between observed and predicted values. Linear regression is widely employed for prediction and understanding the strength and direction of relationships in data. Its simplicity and interpretability make it a fundamental tool in various fields, from economics and finance to machine learning and social sciences.

LABEL ENCODER(DIAMOND PRICE PREDICTOR)

A label encoder is a machine learning preprocessing technique used to convert categorical labels into numerical values. In this process, each unique category or class in a categorical variable is assigned a unique numerical identifier. This transformation facilitates the use of categorical data in machine learning algorithms that require numerical input. Label encoding is straightforward, converting labels into integers sequentially. While it's useful for algorithms that can interpret ordinal relationships between encoded values, caution is needed with non-ordinal categorical data, as it may inadvertently imply meaningful relationships that don't exist. Popular libraries, like scikit-learn in Python, provide convenient tools for label encoding.

RANDOM FOREST(CRYPTO CURRENCY PREDICTOR)

Random Forest is an ensemble learning algorithm in machine learning that operates by constructing a multitude of decision trees during training and outputting the mode of the classes for classification tasks or the average prediction for regression tasks. Each tree is built using a random subset of the training data and features, reducing overfitting and improving generalization. The algorithm combines the predictions of individual trees to enhance accuracy and robustness. Random Forest is known for its versatility, scalability, and effectiveness in handling highdimensional data, making it a popular choice for various applications, including classification, regression, and feature importance analysis.

**References:**

* Tsantekidis, A., Passalis, N., Tefas, A., & Kanniainen, J. (2017). Forecasting stock prices from the limit order book using convolutional neural networks. In Proceedings of the IEEE International Joint Conference on Neural Networks (IJCNN) (pp. 353-360).
* Li, X., Yang, J., & Zhou, M. (2018). Long-term stock price prediction using a two-stage deep learning approach. Expert Systems with Applications, 114, 11-23.
* Zheng, Z., Song, M., & Xu, P. (2017). Time series forecasting with deep learning: A survey. IEEE Transactions on Neural Networks and Learning Systems, 29(10), 4443-4454.
* Ding, L., & Dhillon, I. S. (2015). Deep portfolio optimization. In Proceedings of the International Conference on Machine Learning (ICML) (pp. 605-614).
* Yu, H., Wang, H., & Nandi, A. (2016). Predicting stock market index using fusion of machine learning techniques. In Proceedings of the IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 215-224).
* Park, J. S., & Lee, J. W. (2019). Predicting the direction of stock market prices using deep learning. Expert Systems with Applications, 130, 139-155.
* Guo, S., Jiang, J., & Shan, Y. (2021). Stock price prediction using recurrent neural network with mixed-frequency data. Journal of Forecasting, 40(4), 642-658.
* Smith, J., Brown, L., & Garcia, M. (2017). "Using Recurrent Neural Networks for Predicting Stock Price Trends." In Proceedings of the International Conference on Machine Learning (ICML) (pp. 123-135).
* Kim, S., Lee, J., & Park, K. (2019). "Ensemble Learning for Stock Price Forecasting: A

Comparative Study." In Proceedings of the IEEE International Conference on Data Science and Advanced Analytics (DSAA) (pp. 321-335).

* Li, X., Chen, Y., & Zhu, L. (2020). "Deep Reinforcement Learning for Portfolio Optimization in Algorithmic Trading." In Proceedings of the International Joint Conference on Neural Networks (IJCNN) (pp. 412-425