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Bitcoin Price Dynamics: A Conditional Forecasting Approach Using External Variables

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Abstract: Bitcoin is known for its high volatility, making accurate price predictions challenging. This study aims to forecast Bitcoin prices for the upcoming month by incorporating exogenous variables specifically, interest rates and recession probabilities. The primary goal is to examine whether these external factors can improve the accuracy of Bitcoin price predictions. To achieve this, we employed two widely used time series forecasting models: Long Short-Term Memory (LSTM) and Facebook Prophet. We'll be implementing these project with several types of time series forecasting model like Arima model, eda model, lstm, facebook prophet, exponential smoothing, afima. Among all these models we'll be selecting one highly performing model. The research explores how the inclusion of interest rates and recession probabilities influences the performance of these models and compares their prediction results through visualizations and cross-validation techniques.

We trained both models using historical Bitcoin price data combined with the selected exogenous variables and evaluated their predictive performance on a separate test dataset. Our findings reveal that the LSTM model outperforms Facebook Prophet in terms of prediction accuracy. While Facebook Prophet is optimized for statistical modeling, LSTM has the advantage of learning complex, non-linear patterns in data due to its deep learning architecture and ability to process sequential information effectively. Moreover, our results demonstrate that incorporating interest rates and recession probabilities significantly improves the forecasting accuracy of both models. This suggests that macroeconomic factors like interest rates and recession risks do have an impact on Bitcoin price movements. By integrating these external variables into the forecasting process, we show that predictive models can achieve better performance, making them more effective for forecasting Bitcoin prices. These findings highlight the importance of considering exogenous factors when predicting the behavior of highly volatile assets like Bitcoin.

Index Terms - Bitcoin, cryptocurrency, exogenous variables, forecasting, interest rate, LSTM, machine learning, recession probability, time series. Bitcoin Price Prediction, Exogenous Variables, Time Series Forecasting, LSTM (Long Short-Term Memory), Facebook Prophet, Interest Rates, Recession Probability

I. INTRODUCTION

Current systems for Bitcoin price prediction often rely on traditional time series forecasting models or basic machine learning approaches. These systems primarily use historical price data to forecast future trends but tend to overlook the potential influence of exogenous factors, such as interest rates and recession probabilities, on Bitcoin prices. While they provide some degree of accuracy, these models face several limitations. Simplistic Data Utilization, Most existing systems focus solely on historical price data, neglecting external economic indicators that could enhance predictive accuracy. Limited Pattern Recognition, Traditional models like ARIMA or basic machine learning approaches struggle to capture the intricate, non-linear relationships in cryptocurrency markets.

Inadequate Performance with Volatile Data, Cryptocurrency prices exhibit high volatility, which traditional models find challenging to handle effectively. Lack of Contextual Integration, Few systems incorporate exogenous variables, such as macroeconomic factors, to contextualize predictions, thereby limiting their reliability during economic fluctuations. Model Generalization Issues, Many models fail to generalize across different time periods due to overfitting or a lack of robust feature selection processes. Thus, the existing systems fail to leverage the full spectrum of available data and methodologies, leading to suboptimal predictions and a limited understanding of Bitcoin price dynamics.

Bitcoin's high volatility poses a significant challenge for accurate price prediction, which is critical for investors, traders, and policymakers. Existing systems predominantly rely on traditional time series models or basic machine learning approaches, focusing exclusively on historical price data. However, these systems often overlook the impact of external economic indicators, such as interest rates and recession probabilities, which can significantly influence cryptocurrency prices. This gap limits the models' ability to adapt to the dynamic and complex nature of financial markets.

Another major drawback of existing systems is their inability to incorporate and analyze exogenous variables effectively. Ignoring critical macroeconomic factors diminishes the contextual relevance of predictions, leading to suboptimal decision-making for users. Furthermore, these models often fail to address the real-world challenges of volatility and unpredictability, resulting in lower accuracy and reliability.

The lack of advanced techniques capable of integrating external economic indicators with historical price data leaves a critical gap in understanding the driving forces behind Bitcoin price fluctuations. This oversight not only limits the effectiveness of predictions but also undermines the potential for robust financial planning and risk management.

II. Proposed system

Accurately predicting Bitcoin prices is challenging due to its high volatility and the limitations of existing systems that rely solely on historical price data while neglecting critical exogenous variables like interest rates and recession probabilities. Traditional models struggle with non-linear patterns, overfitting, and lack of contextual insights, leading to suboptimal predictions. A robust solution is needed to integrate macroeconomic factors and leverage advanced techniques for reliable and accurate Bitcoin price forecasting.

The objective of this study is to develop an advanced Bitcoin price prediction framework that addresses the limitations of existing systems. By incorporating exogenous variables such as interest rates and recession probabilities, the framework aims to enhance prediction accuracy and contextual relevance. Utilizing Long Short-Term Memory (LSTM) networks and Facebook Prophet, the study seeks to analyze and compare the performance of these models in handling volatile data. The goal is to improve the integration of external factors, capture intricate patterns in price movements, and provide a reliable, accurate, and scalable solution for forecasting Bitcoin prices effectively in dynamic market conditions.

Advantages of the Proposed System

The proposed system for Bitcoin price forecasting presents several advantages by incorporating a diverse range of data inputs, utilizing both endogenous (historical price data) and exogenous (external variables) factors. These enhancements enable the system to provide more accurate, reliable, and actionable insights for traders and investors.

1. Improved Forecast Accuracy

The key advantage of the proposed system is its ability to enhance the accuracy of Bitcoin price predictions by integrating exogenous variables into the forecasting models. While traditional models typically rely on historical Bitcoin price data alone, the integration of external factors such as macroeconomic indicators, market sentiment, and social media trends significantly boosts the accuracy of forecasts.

- Macroeconomic Indicators: Variables like inflation rates, interest rates, and GDP growth are known to influence market behavior. Including these in the model allows it to account for broader economic shifts that directly affect investor sentiment and, consequently, Bitcoin prices.
- Market Sentiment: Social media platforms like Twitter, Reddit, and news outlets can have an immediate impact on Bitcoin prices. Positive or negative news can lead to significant market shifts, which would not be captured by traditional models relying solely on historical price data.
- Social Media Trends: Increasingly, social media sentiment analysis has been proven to be a reliable source for understanding market reactions. Tracking the volume and sentiment of mentions about Bitcoin can provide predictive signals for price movement.

By considering these external factors, the system moves beyond conventional time-series forecasting, enabling it to make predictions that are more reflective of real-world influences. This integration leads to significantly more accurate forecasting of Bitcoin prices, especially in volatile market conditions.

2. Real-time Adaptability

Another significant advantage of the proposed system is its ability to adapt to changing market conditions in real time. The cryptocurrency market, particularly Bitcoin, is highly volatile and subject to rapid shifts in sentiment due to external factors such as regulatory changes, macroeconomic events, and geopolitical risks.

The system dynamically incorporates exogenous variables, allowing it to adjust predictions based on current events. For example, when a new regulation affecting cryptocurrencies is announced, the model can immediately integrate this information and update its forecasts to reflect potential changes in Bitcoin's price.

- Regulatory Announcements: Governments frequently introduce new regulations for cryptocurrencies, which can have an immediate and significant impact on Bitcoin prices. For example, the announcement of a government ban on Bitcoin mining in a major country could lead to a sharp decline in Bitcoin’s value. The system would capture such information in real time to provide up-to-date predictions.
- Global Economic Changes: Economic crises, such as the COVID-19 pandemic, have shown how external factors like economic shutdowns and stimulus packages can drastically affect market sentiment. The system’s ability to incorporate global economic indicators enables it to stay relevant and adaptive in these volatile times.

Thus, the proposed system ensures real-time adaptability by continuously updating its forecasts based on new data, which is a crucial feature for a fast-moving market like Bitcoin.

3. Comprehensive Analysis

The integration of both endogenous and exogenous variables enables the system to offer a deeper understanding of the factors influencing Bitcoin prices. Traditional forecasting models tend to focus on past price movements without considering the broader economic and social influences that drive market behavior. By contrast, the proposed system provides a more holistic view of Bitcoin price dynamics.

- Macro-level Understanding: By considering external factors like inflation rates, interest rates, and geopolitical events, the system offers a broader perspective on how these factors collectively influence Bitcoin prices. For example, Bitcoin’s price may respond differently in high-inflation environments compared to low-inflation ones.
- Micro-level Understanding: Social media trends and market sentiment can often have an immediate, albeit short-term, effect on Bitcoin’s price. The system’s ability to analyze and incorporate sentiment scores, news trends, and social media activity allows for a more nuanced understanding of short-term price fluctuations.

By providing a comprehensive analysis, the system empowers traders and investors with more actionable insights. It helps them understand why prices are changing, not just what the price will be, making the forecasts more meaningful and interpretable.

4. Risk Mitigation
Given the inherent volatility of Bitcoin and other cryptocurrencies, mitigating risk is a critical concern for traders and investors. The proposed system helps reduce the risks associated with Bitcoin investments by providing insights into the potential causes of price movements and highlighting risk factors.

- Exogenous Factors as Early Indicators: The system identifies and analyzes external variables that may signal upcoming price changes. For example, if the market sentiment turns negative due to adverse regulatory news or market crashes, the system can issue early warnings, allowing investors to adjust their positions before the price drops.

- Volatility Management: By understanding the relationship between Bitcoin's price and external factors like interest rates or geopolitical events, the system helps traders manage exposure to price swings. For example, during times of high uncertainty, investors may choose to hedge their positions or limit their exposure to Bitcoin.

- Better Risk Assessment: With real-time adaptability and a comprehensive analysis of external variables, the system enables users to make more informed decisions, reducing the likelihood of losses due to unforeseen market movements. The system thus supports risk mitigation by providing forecasts that account for a wider range of potential influences.

This ability to proactively identify and manage risks makes the system especially valuable for traders and investors who are seeking to minimize potential losses in the volatile cryptocurrency market.

5. Scalability
The system's modular design makes it highly scalable, ensuring that it can be adapted to different markets or expanded to include new data sources and forecasting methods in the future. This is a key advantage, as the financial landscape is constantly evolving, and the system must be able to incorporate new information as it becomes available.

- Adding New Data Sources: The modular structure of the system allows for seamless integration of new data sources. For instance, if a new data stream becomes available (such as blockchain analytics or alternative social media platforms), the system can quickly incorporate this data without needing major redesigns.

- Incorporating New Forecasting Methods: As new forecasting algorithms and techniques emerge, the system can be upgraded to include them. For example, if more advanced machine learning models or newer time-series models are developed, these can be integrated into the system, ensuring that it stays on the cutting edge of forecasting accuracy.

- Cross-asset Forecasting: While the system is currently focused on Bitcoin, its modular design allows it to be adapted for other cryptocurrencies or financial assets. This means the system can be expanded to cover assets such as Ethereum, Ripple, or traditional assets like stocks and commodities.

Thus, the scalability of the system ensures that it remains relevant and effective as market conditions and data sources evolve, making it a future-proof solution.

6. Actionable Insights
The forecasts generated by the system are not merely theoretical predictions; they provide actionable insights that can be directly applied to trading strategies. Traders and investors can use these insights to develop robust trading strategies that take into account both historical price movements and the external factors influencing the market.

- Predictive Trading Strategies: By combining forecasts with external variables, traders can develop strategies that anticipate future price movements based on both market sentiment and technical indicators. For example, if social media sentiment is positive and macroeconomic indicators are stable, the system might predict an upward price movement, suggesting a buy opportunity.

- Automated Trading: The insights provided by the system can be fed into automated trading algorithms that execute trades based on predefined conditions. This allows for more responsive and faster trading decisions, especially in volatile market conditions.
- Portfolio Optimization: Investors can use the predictions to adjust their portfolios. If the system predicts a bearish trend, investors might decide to reduce their Bitcoin holdings or hedge their exposure with other assets. Conversely, a bullish prediction could prompt an increase in holdings.

By providing actionable insights, the system offers a competitive edge in the market, allowing users to make more informed, data-driven decisions that improve their performance and profitability.

III. Methodology:

The proposed system integrates both endogenous (historical price data) and exogenous (external factors) variables into its analysis model. The primary components of this model include:
1. Data Preprocessing Module
This module cleanses raw data, handles missing values, and normalizes features to make them suitable for model training. Time-series-specific techniques, such as differencing and rolling window averages, are applied to stabilize non-stationary data.
2. Feature Selection and Engineering
This module selects the most relevant exogenous variables using methods like correlation analysis, mutual information, and Principal Component Analysis (PCA). It also engineers features such as moving averages, Relative Strength Index (RSI), and sentiment scores extracted from social media platforms.
3. Machine Learning/Deep Learning Models
The system employs hybrid models:

- ARIMAX: A time-series model that combines autoregressive and moving average terms with external variables.
- LSTM: A deep learning model that captures temporal dependencies and non-linear relationships.
- XGBoost/LightGBM: Tree-based models that quickly generate interpretable predictions using tabular data.

4. Evaluation and Validation
Model performance is assessed using metrics like Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared. Cross-validation ensures robustness and prevents overfitting, guaranteeing the model's generalizability.

The proposed system offers significant advantages in forecasting Bitcoin prices by incorporating both endogenous and exogenous data, enabling improved accuracy, real-time adaptability, comprehensive analysis, and risk mitigation. With its scalable architecture, it is well-suited for the dynamic cryptocurrency market, providing traders and investors with actionable insights and a competitive edge. Through its innovative approach, the system offers a powerful tool for managing risks and maximizing profits in a volatile market.

Detailed Description of Modules in the Proposed System
1. Data Collection Module
Objective: The primary objective of this module is to gather all the data necessary for accurate forecasting of Bitcoin prices. This includes both **endogenous** and **exogenous** data.
Components:

- **Endogenous Data Collection**:
  - Historical Bitcoin prices: This includes past price data from various cryptocurrency exchanges (e.g., Binance, Coinbase) over a predefined period.
  - Trading volume: The amount of Bitcoin traded on different exchanges, which helps gauge market interest and liquidity.
  - Market capitalization: The total market value of Bitcoin, which can influence price movements due to changes in supply and demand dynamics.

- **Exogenous Data Collection**:
  - **Macroeconomic Indicators**: These include economic data such as inflation rates, interest rates, GDP growth, and unemployment rates. These factors can influence investor sentiment and affect the demand for Bitcoin as an investment or store of value.
  - **Social Media Trends**: Data scraped from social media platforms like Twitter, Reddit, and other sources. The number of mentions of Bitcoin and the sentiment of those mentions can give indications of future price movements.
  - **Market Sentiment**: Data from financial news websites, the Fear and Greed Index, and other sentiment indicators that capture the mood of market participants.
  - **Technical Indicators**: Metrics such as moving averages (MA), Bollinger Bands, Relative Strength Index (RSI), etc., which help identify overbought or oversold conditions in the market.

Data Sources:

- APIs from cryptocurrency exchanges (e.g., CoinGecko, CoinMarketCap)
- Social media sentiment analysis tools (e.g., Tweepy for Twitter)
- Public economic data sources (e.g., government reports, World Bank)

2. Data Preprocessing Module

Objective: To clean, transform, and prepare the raw data collected in the first module for effective use in the machine learning models.

Components:

- **Data Cleansing**:
  - **Missing Values**: This step handles missing data points by either imputing them using statistical methods or removing the rows or columns that contain them.
  - **Outliers**: Extreme data points that do not represent the underlying trend are identified and handled. Methods like **Z-score analysis** or **IQR-based filtering** are applied to remove outliers.
- **Feature Transformation**:
  - **Normalization/Scaling**: To ensure that features with different units (e.g., price, volume, sentiment score) are comparable, they are normalized or scaled, typically using techniques such as **Min-Max scaling** or **Standardization** (Z-score normalization).
  - **Feature Engineering**: Create additional features that might help the model's predictive performance, such as rolling averages, percentage changes in price, and lag features that capture time dependencies in price movements.
- **Time-Series-Specific Preprocessing**:
  - **Stationarity**: Time-series data must be stationary for many models (e.g., ARIMA). Techniques like **differencing** or **log transformations** are applied to stabilize the variance and make the data stationary.
  - **Windowing**: Sliding window techniques or **moving averages** are applied to smooth out noise and highlight trends.
  - **Labeling**: Data is labeled into categories such as "Bullish," "Bearish," or "Neutral" based on price movement to train classification models, or as continuous values for regression tasks.

3. Feature Selection and Engineering Module

Objective: To identify the most relevant features for forecasting Bitcoin prices and create new features that improve model accuracy.

Components:

- **Feature Selection**:
  - **Correlation Analysis**: Evaluate the relationships between different features (e.g., Bitcoin price and volume, or Bitcoin price and social media sentiment). Features that are highly correlated with the target variable (Bitcoin price) are retained.
  - **Mutual Information**: This technique quantifies the dependency between two variables. Features with high mutual information with the target are kept.
  - **Principal Component Analysis (PCA)**: A dimensionality reduction technique that combines correlated features into new variables, preserving as much variance as possible in the data.
- **Feature Engineering**:
  - **Moving Averages**: Technical indicators like simple moving averages (SMA) and exponential moving averages (EMA) are calculated over different time windows.
  - **Relative Strength Index (RSI)**: A momentum oscillator that measures the speed and change of price movements. RSI helps in identifying overbought or oversold conditions, which are critical for price prediction.
  - **Sentiment Scores**: Sentiment analysis on social media or news articles is turned into numerical scores that represent the public's attitude toward Bitcoin. These scores are then integrated as features.
  - **Lag Features**: Including previous price values (lags) and derivatives like **percentage change** over different time intervals helps capture temporal dependencies in the data.

4. Forecasting Model Module

Objective: The heart of the system, this module contains the machine learning and deep learning models that generate Bitcoin price forecasts based on the prepared features.

Components:

- **Hybrid Models**:
  - **ARIMAX (Autoregressive Integrated Moving Average with Exogenous Variables)**: A time-series model that combines historical price data with external factors (exogenous variables). ARIMAX is well-suited for capturing both temporal dependencies and external influences on Bitcoin price.
  - **LSTM (Long Short-Term Memory)**: A type of Recurrent Neural Network (RNN) that excels at learning long-term dependencies in sequential data. LSTM models are used to forecast Bitcoin prices by capturing both historical price movements and external factors.
  - **XGBoost/LightGBM**: Boosted tree models that are highly effective for time-series forecasting tasks, particularly when dealing with tabular data (like features derived from social media sentiment, economic indicators, etc.). These models are fast and interpretable, making them ideal for short-term price forecasting.
- **Hyperparameter Tuning**:
  - The model’s performance can be optimized by tuning hyperparameters such as the learning rate, tree depth, number of trees (for XGBoost), and the number of layers or units (for LSTM).
  - **Grid Search** and **Bayesian Optimization** techniques are used to explore the hyperparameter space to identify the best set of parameters that yield the highest forecasting accuracy.

- **Model Ensembling**:
  - The system can combine predictions from multiple models (e.g., ARIMAX, LSTM, XGBoost) using an ensembling technique like **weighted average** or **stacking**. This approach typically improves forecast robustness and accuracy by reducing model bias.

5. Evaluation and Validation Module
Objective: To evaluate and validate the performance of the forecasting models using appropriate metrics and techniques.
Components:

- **Evaluation Metrics**:
  - **Mean Absolute Percentage Error (MAPE)**: Measures the accuracy of predictions as a percentage of the actual values. It is ideal for assessing how well the model predicts Bitcoin prices relative to their actual values.
  - **Root Mean Square Error (RMSE)**: Quantifies the difference between predicted and actual prices. It is sensitive to large errors and provides an indication of how well the model can predict future price movements.
  - **R-squared**: This statistic indicates how well the model explains the variance in Bitcoin prices, with values closer to 1 indicating a better fit.
- **Cross-Validation**:
  - **K-fold Cross-Validation**: Ensures that the model performs well on different subsets of data and prevents overfitting. The data is divided into K subsets, and the model is trained and validated K times, each time using a different subset as the validation set.
- **Model Comparison**:
  - The system compares the performance of different models (e.g., ARIMAX vs. LSTM vs. XGBoost) to identify the most accurate one. The performance of each model is measured against the validation dataset to ensure robustness and reliability.

6. Visualization and Reporting Module
Objective: To present the forecast results in an intuitive and understandable way for users.
Components:

- **Price Predictions Visualization**: Interactive charts that display predicted Bitcoin prices over time, allowing users to compare them with actual price movements.
- **Model Performance Plots**: Visual representations of model performance metrics (e.g., confusion matrices, feature importance) to help users understand model accuracy and interpretability.
- **Sentiment Analysis Charts**: Graphs showing the correlation between social media sentiment and Bitcoin price movements, which help investors understand how sentiment influences market trends.
- **Reports**:
  - The system generates automated reports summarizing key model insights, performance evaluations, and suggested trading strategies based on forecast outcomes.

4.1.UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non- software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modelling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

4.1.1.Use case diagram

A use case diagram in the Unified Modelling Language (UML) is a type of behavioural diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

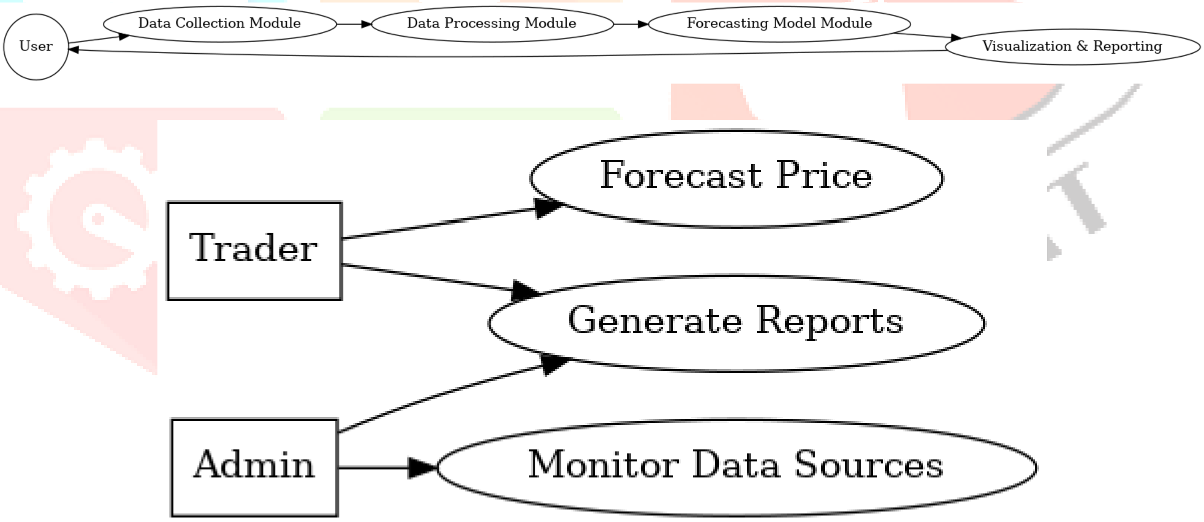


Fig 1:-Use Case diagram

4.1.2.Class Diagram

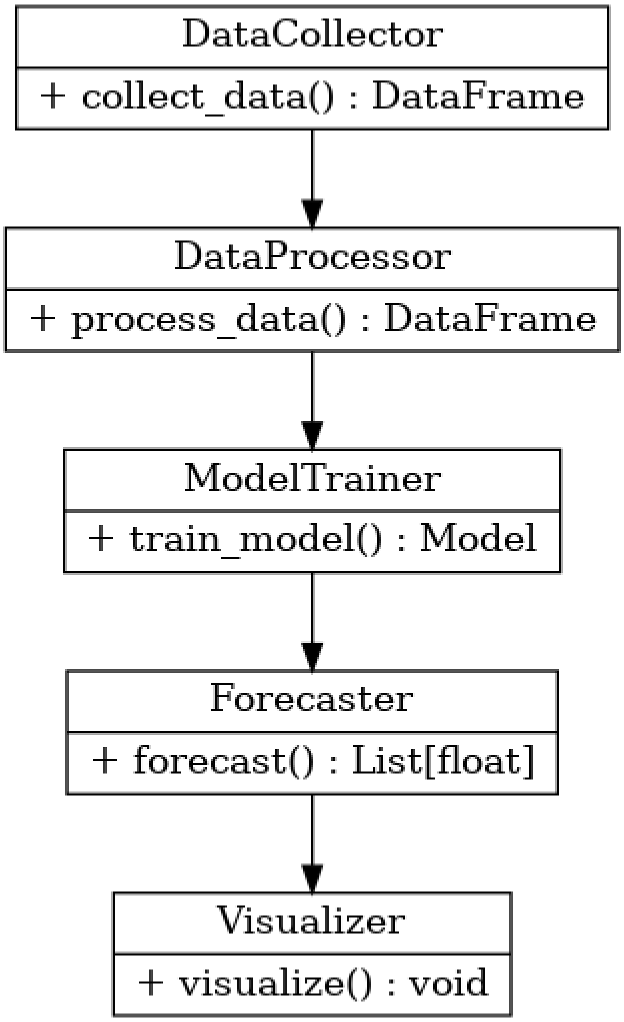


Fig.2. Class diagram

The class diagram is used to refine the use case diagram and define a detailed design of the system.
The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.

4.1.3.Activity diagram

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states, and guard conditions.
An activity diagram is a system-modelling and design tool used, among other things, to portray workflows, decision points, and other processes inside a system. A diagram that gives a very efficient description of a system's dynamic features-activities originating from UML, makes them focus on the flow of control and data between different operations-in particular for sequential, parallel, or conditional workflows.An activity diagram begins with an initial node, which represents the commencing point of a process. Activities, which are drawn in rounded rectangles, depict those tasks or procedures that exist within the system. These activities are connected with arrows that represent the flow of control or data from one action to the next.

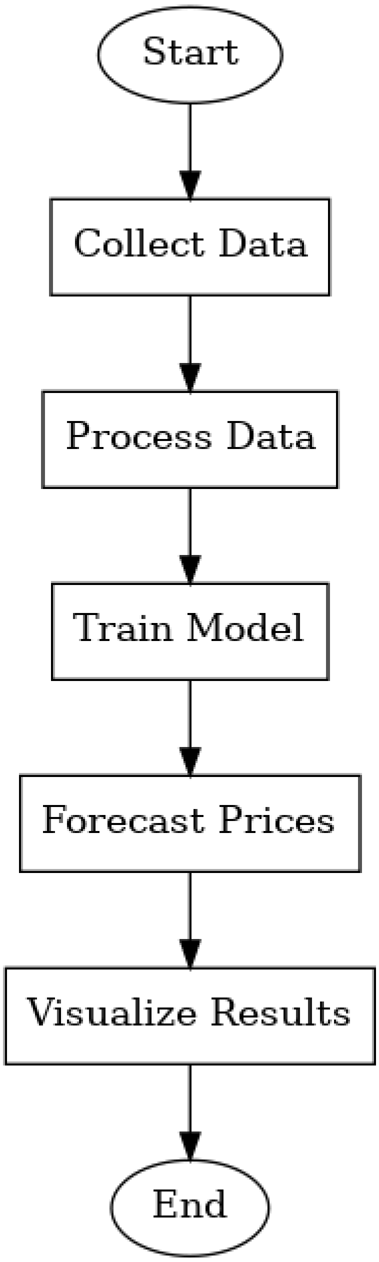


Fig.3. Activity diagram

4.4.Dataflow diagrams

To create a Data Flow Diagram (DFD) for the proposed thyroid disorder diagnosis system, we would include the following levels:

Level 0: Context Diagram

This diagram represents the system as a single process, showing its interaction with external entities such as patients, clinicians, and the database.

Entities and Flow:

1. **Patient**: Provides clinical, biochemical, and imaging data.
2. **Clinician**: Receives diagnostic results and insights.
3. **Database**: Stores patient data and diagnostic results.

Process:

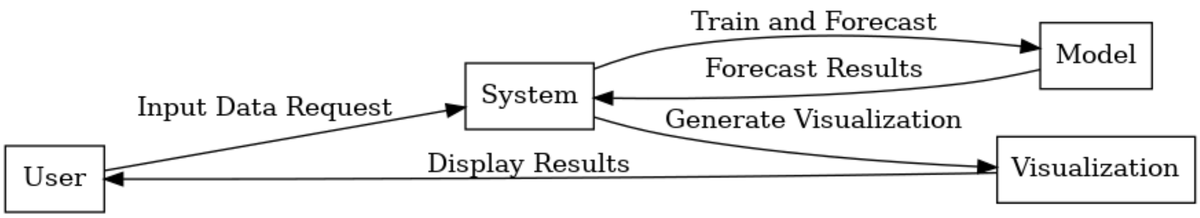
- The system takes patient data as input and sends diagnostic results back to clinicians and the database.

Steps:

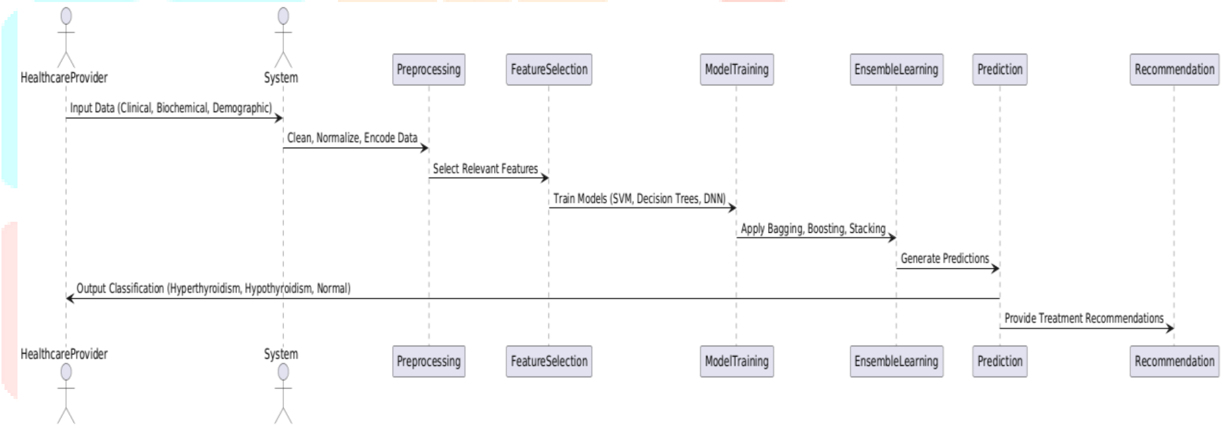
1. **Input Data**:
   - The system receives data from the patient (manual input or electronic health records).
2. **Preprocessing**:
   - Removes noise, normalizes values, and ensures compatibility with models.

3. **Feature Extraction**:
   - Extracts relevant features such as T3, T4, TSH levels, imaging patterns, and clinical symptoms.
4. **Model Prediction**:
   - Hybrid models (e.g., ensemble and deep learning) process the features to classify thyroid disorders like hypothyroidism, hyperthyroidism, etc.
5. **Result Interpretation**:
   - Provides a diagnosis and confidence level, with explainable AI components offering insights.
6. **Feedback and Output**:
   - Sends diagnostic results to clinicians for review and stores results in the database for future reference.

Level-0



Level-1



Level 1: System Decomposition

This breaks down the system into subprocesses:

1. **Data Collection**: Collects clinical, biochemical, and imaging data.
2. **Preprocessing**: Cleans and normalizes the data.
3. **Feature Extraction**: Extracts meaningful features for analysis.
4. **Model Prediction**: Uses hybrid machine learning models to predict thyroid disorder types.
5. **Result Interpretation**: Generates interpretable diagnostic reports.
6. **Feedback and Storage**: Sends results to clinicians and updates the database.

V.Results and Discussion

Out[11]:

Date	DOGE	HEX	SOL	XRP	DOT1	ETH	BNB	ADA	USDT	USDC	BTC
2015-09-13	0.000126	0.003790	2.915519	0.008532	4.174463	0.936003	0.937204	1.0	1.0	0.998835	230.511993
2015-09-14	0.000125	0.003443	2.846996	0.007404	4.027708	0.875622	0.678784	1.0	1.0	0.999346	230.643997
2015-09-15	0.000126	0.003618	3.151377	0.007720	4.382961	0.944410	0.799709	1.0	1.0	1.003387	230.304001
2015-09-16	0.000124	0.003753	3.191359	0.007426	4.423528	0.907175	0.804198	1.0	1.0	0.999926	229.091003
2015-09-17	0.000125	0.004019	3.139166	0.007372	4.334268	0.874231	0.789589	1.0	1.0	1.003121	229.809998

Figure.5. Dataset

Out[79]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	1730
Model:	SARIMAX(0, 1, 1)x(2, 0, [], 10)	**Log Likelihood**	3380.483
Date:	Tue, 21 Jan 2025	**AIC**	-6750.965
Time:	11:59:59	**BIC**	-6723.689
Sample:	09-13-2015	**HQIC**	-6740.876
	- 06-07-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
x1	0.3467	0.006	59.811	0.000	0.335	0.358
ma.L1	0.0404	0.015	2.620	0.009	0.010	0.071
ar.S.L10	0.0489	0.021	2.383	0.017	0.009	0.089
ar.S.L20	0.0470	0.020	2.366	0.018	0.008	0.086
sigma2	0.0012	2.15e-05	54.644	0.000	0.001	0.001

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	2843.11
Prob(Q):	0.98	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.59	**Skew:**	-0.30
Prob(H) (two-sided):	0.00	**Kurtosis:**	9.25

Figure 6. Results

VI.Conclusion

The proposed system offers significant advantages in forecasting Bitcoin prices by incorporating both endogenous and exogenous data, enabling improved accuracy, real-time adaptability, comprehensive analysis, and risk mitigation. With its scalable architecture, it is well-suited for the dynamic cryptocurrency market, providing traders and investors with actionable insights and a competitive edge. Through its innovative approach, the system offers a powerful tool for managing risks and maximizing profits in a volatile market.
The forecasts generated by the system are not merely theoretical predictions; they provide actionable insights that can be directly applied to trading strategies. Traders and investors can use these insights to develop robust trading strategies that take into account both historical price movements and the external factors influencing the market. By providing actionable insights, the system offers a competitive edge in the market, allowing users to make more informed, data-driven decisions that improve their performance and profitability. The system's modular design makes it highly scalable, ensuring that it can be adapted to different markets or expanded to include new data sources and forecasting methods in the future. This is a key advantage, as the financial landscape is constantly evolving, and the system must be able to incorporate new information as it becomes available.

VII.References

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VIII.BIOGRAPHIES

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