THE ESTABLISHMENT OF A ROBUST FRAMEWORK FOR THE ISSUANCE OF CENTRAL BANK DIGITAL CURRENCY (CBDC) IN MALAYSIA

Abstract. *With the advancement of different cryptocurrencies, such as Libra, Ethereum, and Bitcoin, the financial system has undergone some revolutionary changes around the globe as they leverage decentralized platforms such as blockchain to provide rights like ownership and payback from anticipated earnings. The Central Bank of Malaysia (Bank Negara Malaysia) has begun research and developing a cross-border wholesale CBDC, which is scheduled to take place in September 2021. This study establishes a robust framework by leveraging the machine-learning technique that determines the most critical factors leading to CBDC issuance in Malaysia. Treating the overall CBDCPI as an objective variable, the accuracy obtained through the random forest is 83% and 80% in XGBoost. This study explored a new research frontier by creating two more machine-learning models that treated retail and wholesale CBDCPI as objective variables. The data to use in the process is gathered from various official sources such as BIS, IMF, and World Bank. The circulation of cash, the prevalence of cryptocurrencies, and the effect of CBDC on international trade are some of the most critical factors determining whether or not CBDC will be issued in Malaysia.*

Keywords– *Machine learning, Random Forest, XGBoost, Central Bank Digital Currency.*

1. INTRODUCTION

Over the course of the past, various new systems of payment have emerged to satisfy the requirements of society. The evolution of money has resulted in the creation of banknotes, credit cards, checks, and coins. Printed money is giving way to digital currency as technology advances. Because of this, distributed ledger technology and other advancements in the world of finance allowed for the launch of digital currencies. Moreover, the fear of different cryptocurrencies, such as Libra, Ethereum, and Bitcoin, taking control of the financial system has motivated the Central Bank to instantiate the issuance of CBDC.

In a report published in 2020, Bank Negara Malaysia displayed a comparison between digital assets (Cryptocurrency, stablecoins) and fiat currency. This report explains that digital assets can be classified as exchange, utility, or security tokens depending on whether they provide rights of ownership, return of a principal sum, or participation in future earnings. The term "Cryptocurrency" is commonly used to refer to these privately issued digital assets. Cryptocurrencies have shown promise in several areas but also major drawbacks. The high degree of price fluctuation is one of the primary downsides. In 2023, for instance, Bitcoin's price may fall by 40%, from its current $17,000 to $10,000 [1].Moreover, cryptocurrencies are prone to slow transaction rates as Bitcoin can process only 3.3 transactions per second, whereas conventional systems can process more than 3000 transactions per second. Therefore, Stablecoins, a new type of digital currency created to counteract the drawbacks and volatility of cryptocurrencies. Some stablecoins have a value connected to tangible assets like gold, while others have value anchored to national fiat currencies. As a result, it's possible that stablecoins will someday find widespread use in retail payment systems.

To combat privately issued digital currencies and their impact on Malaysia's economy, the Central Bank of Malaysia (Bank Negara Malaysia) has begun research and development of a cross-border wholesale CBDC, which is scheduled to take place in September 2021. The first phase of BNM's CBDC project initiatives includes easing international transactions between financial institutions and creating a shared platform for cross-border settlements. The initiative is Project Dunbar, which leverages the benefits of multiple CBDCs (mCBDC) on DLT platforms partnering with BIS Innovation Hub, Reserve Bank of Australia, Bank Negara Malaysia, Monetary Authority of Singapore, and South African Reserve Bank. Moreover, the implementation of domestic wholesale CBDC and retail CBDC, respectively, is included in the last two phases of the proof-of-concept roadmap.

CBDC is typically issued in response to local circumstances due to its strong potential as a beneficial instrument in accomplishing policy priorities.According to the Central Bank of Malaysia (Bank Negara Malaysia), the circulation of cash, the prevalence of the use of cryptocurrencies, and the effect of CBDC on international trade are some of the most critical factors that will determine whether or not CBDC will be issued in Malaysia.In addition, factors like the internet's infrastructure, economic growth rate, and demographics can influence the distribution of CBDC. This study establishes a robust framework by leveraging the machine-learning technique that determines the most critical factors leading to CBDC issuance in Malaysia. The data to use in the process is gathered from various official sources such as BIS, IMF, and World Bank. The problem will be treated as a classification problem taking overall, retail and wholesale CBDC project index as target variables. Hence, the Random forest classifier and XGBoost classifier will be used to create three machine learning models and extract the most important features that drive a country to accelerate the effort of CBDC issuance.

2. REVIEW AND PREVIOUS WORKS

2.1. Definition of CBDC.

CBDC is often defined as digital legal tender. IMF proposes this definition [2]. According to Brookings International, A central bank digital currency (CBDC) is a digital version of a central bank-issued fiat currency [3]. European Central Bank defines CBDC as an electronically administered currency issued by a central bank and usable by the general public [4]. Bank for International settlements defines CBDC as electronic money issued by the central bank, which would be available to the general public at retail. At the same time, wholesale CBDCs could be a fresh mechanism for bank settlement [5].

2.2. CBDC implementation

CBDC is a new type of central bank electronic liability that may be used as a payment and value storage while retaining most of M0 and M1's desirable properties. As mentioned in [6], CBDC should serve as a medium of exchange, store of value, unit of account, and standard for deferred payments.Moreover, CBDC has two components: the business structure and the ledger structure [6]. CBDC ledgers are token-based or account-based. An account-based system seems most appropriate when access and identity verification are priorities for wholesale CBDC (interbank settlements). A user must have their identification as the account holder validated by a third party and adequate funds to make a payment. Whereas for token-based CBDC, by signing a transaction using a token's private key, customers can use token-based verification to prove their identity. Some token-based infrastructures also offer account-based and multifactor authentication.

However, the expanding CBDC-related literature has zeroed in on two key concerns: The first concern is whether or not CBDCs are preferable as a replacement for physical currency and the method by which central banks should generate digital currency for retail use [7] [8].The other concern is how to deal with the potential liabilities, and volatility CBDCs may pose to the financial and monetary systems. [9] [10].The analysis [11] demonstrates that distinct strategies for adopting CBDCs demand distinctive actions from central banks. To ignite people's interest in CBDC, the monetary authorities should take action by lowering interest rates and raising deposit rates. The study also shows that the CBDC's implications on the financial and banking system depend on the degree of convergence between the two. Changes to the circulation of money are inevitable with the widespread adoption of CBDC in retail, as digital currency gradually replaces traditional forms of payment. Because of this, the central bank will set a fair interest rate and deposit rate, and the quantity of newly created currency will eventually decrease. As a result, commercial banks will face more competition if the deposit rate at central banks is high. In addition, wholesale CBDC will impact the Real-time gross system by replacing it with cross-border CBDC. International trade will be conducted by it. Furthermore, wholesale CBDC can offer continuous, around-the-clock support to the general public, reduce the number of middlemen in trade, and upgrade the existing system to support a unified group of payment standards. However, It may be too expensive for countries with weak financial systems to implement.

In peer-to-peer lending, big data and machine learning are used in highly complex ways to assess customer data [12]. Based on detailed loan transaction data from a different Chinese fintech industry frontrunner, [13] finds that, as opposed to conventional models, machine learning algorithms provide more accurate default risk assessments of debtors, specifically when a negative supply shock causes output to fall and prices to rise. Similarly, as mentioned in [2], demand for CBDC in specific regions or industries may be predicted using machine learning algorithms based on classification tasks. The data gathered in the detailed analysis would result in a better understanding of the CBDC and could help forecast and develop macroeconomic stimulus. For example, central banks might utilize the information gathered to finance management and deposits or calculate the natural money supply using machine learning or other sophisticated quantitative models.

2.3. Pros and cons of CBDC.

As mentioned in [14], CBDC can decrease the demand for paper notes as the issuance of it will encourage more people to keep their money in the banks, forcing banks to decrease deposit rates. Moreover, it was speculated that the CBDC issuance fiscal policy would lead to market instability. However, [15] proposed that CBDC would improve market stability by increasing central bank deposits via pass-through funding.

Central banks have significant concerns about the prospect of people choosing CBDC accounts over commercial bank accounts and the impact on the broader financial system. As [16] explored that a digital currency issued by state-owned banks would discourage people from keeping deposits in commercial banks, and people would lean towards central banks.

Therefore, to keep a balance, it is necessary that Commercial banks and financial service providers are responsible for issuing wallets and managing apps, while central banks are responsible for issuing the value of CBDC and authenticating it [17]. According to [18], account-based CBDCs would let central banks work as middlemen between commercial banks and financial service providers. This would allow the public to directly maintain an account in the state-owned bank. All in all, the promoters of CBDC argue that CBDC will broadly make the banking and transaction processes safer and more efficient [19].

3. DATA AND METHODOLOGY

The primary purpose of our research is to design a solid infrastructure for the issuance of CBDC in Malaysia. However, due to the fact that CBDC is the subject of our study, it is necessary for us to collect data that has an effect on CBDC. Therefore, this can be boiled down to identifying the most significant influence factors impacting a country's technological faculties and good governance and utilizing retail or wholesale CBDC project index score as the target variable. To this end, we use ML methods for forecasting the CBDCPI and data mining, the most crucial factors for our model construction.

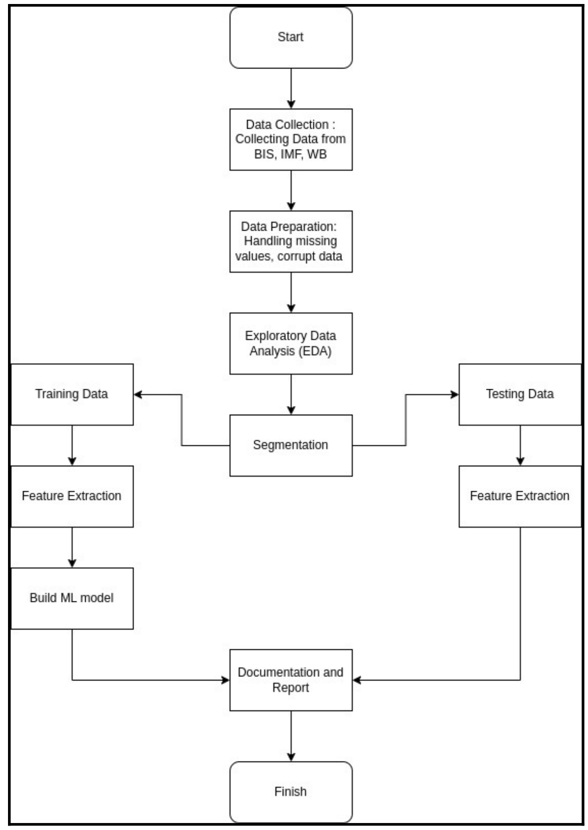

Fig. 1 Summary of Methodology

3.1. Data Description

The first step is to gather relevant data when beginning a new project. Collecting relevant information from various resources to assess potential outcomes and patterns for research with the help of validation techniques is known as data collection. After collecting data, a data analyst must perform data cleaning and feature engineering to find the solution to the research problem. The data analyst's position is crucial to basic research since it streamlines and improves the precision of analyzing data. It allows the researchers to understand data so they don't miss any information. To make effective data-driven selections, the data must be meaningful and reliable for data analysis.

Gathering appropriate domain datasets is the starting point for each ML-based research. We gather information for our datasets from the World Bank, the IMF, and a BIS working paper. Then all of the datasets are merged into one by using python libraries. Figure (Fig.2) and figure (Fig. 3) show that the dataset spans from 1990 to 2021 and includes more than 190 separate nationalities and territories with 24 different variables.

```
print(df_3.head(2))

  ISO2                country_name  project_score_overall  \
0   AD                     Andorra                    NaN
1   AE  United Arab Emirates (the)                    2.0

   project_score_retail  project_score_wholesale  search_interest_normalized  \
0                   NaN                      NaN                   -0.625377
1                   0.0                      2.0                    2.708119

   central_bankers_speech_stance_index_normalized  search_interest  \
0                                       -0.283358         0.000000
1                                        3.580257        20.394737

   central_bankers_speech_stance_index  Mobile_Cellular_sub  \
0                                  0.0           106.194651
1                                  1.0           201.706234

   Financial_Development_Index  Trade (% of GDP)  GDP(USD)  \
0                     0.000000          0.000000  39932.59
1                     0.481569        168.277133  40322.40

   VoiceandAccountability  GovernmentEffectiveness  \
0                    1.11                     1.90
1                   -1.12                     1.39

   Broadband_Subscribsions(per100people)  Innovation_Score  Account_Ownership  \
0                              45.577432              0.00                NaN
1                              27.672626             42.56             86.975

   Secure_Internet_Servers  Trade_Openness  Access_to_Electricity  \
0              11698.85737       65.805371                  100.0
1               1600.51494      169.527636                  100.0

   Individual_Internet_Users  Regulatory quality  \
0                  90.633734                1.17
1                  96.603986                1.00

   Population ages 65 and above (% of total population)
0                                                 NaN
1                                            1.197829
```

Fig. 2. All columns are displayed with the first two rows.

```
df_3.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194 entries, 0 to 193
Data columns (total 24 columns):
 #   Column                                                Non-Null Count  Dtype
---  ------                                                --------------  -----
 0   ISO2                                                  193 non-null    object
 1   country_name                                          194 non-null    object
 2   project_score_overall                                 175 non-null    float64
 3   project_score_retail                                  175 non-null    float64
 4   project_score_wholesale                               175 non-null    float64
 5   search_interest_normalized                            194 non-null    float64
 6   central_bankers_speech_stance_index_normalized        194 non-null    float64
 7   search_interest                                       194 non-null    float64
 8   central_bankers_speech_stance_index                   194 non-null    float64
 9   Mobile_Cellular_sub                                   194 non-null    float64
 10  Financial_Development_Index                           194 non-null    float64
 11  Trade (% of GDP)                                      194 non-null    float64
 12  GDP(USD)                                              194 non-null    float64
 13  VoiceandAccountability                                194 non-null    float64
 14  GovernmentEffectiveness                               194 non-null    float64
 15  Broadband_Subscribsions(per100people)                 194 non-null    float64
 16  Innovation_Score                                      156 non-null    float64
 17  Account_Ownership                                     133 non-null    float64
 18  Secure_Internet_Servers                               181 non-null    float64
 19  Trade_Openness                                        178 non-null    float64
 20  Access_to_Electricity                                 180 non-null    float64
 21  Individual_Internet_Users                             179 non-null    float64
 22  Regulatory quality                                    177 non-null    float64
 23  Population ages 65 and above (% of total population)  168 non-null    float64
```

Fig. 3. Information of all variables and their type.

As mentioned in [20], the following criteria can categorize features of the dataset: the availability of internet infrastructure, the rate of economic growth and financial integration, the nature of institutions, the culture of invention, demographics, and the frequency of international trade.

China's central bank first initiated CBDC development in 2014, and Sweden's central began researching the establishment of digital currency in 2017 [21]. Therefore, we have only covered the average of each feature from 2015-2021, although our dataset contains data ranging from 1990 to 2021.

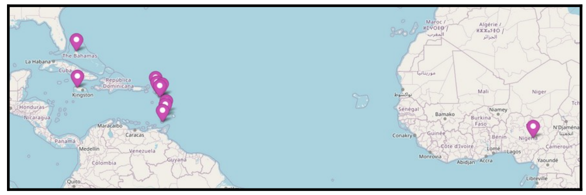

Fig. 4. Countries with live CBDC as of July,2022 [5].

Figure 4 displays Nigeria, Bahamas, Jamaica, and countries that receive their currency from ECCB (Anguilla, Antigua and Barbuda, Commonwealth of Dominica, Grenada, Montserrat, Saint Christopher (St Kitts) and Nevis, Saint Lucia, and Saint Vincent and the Grenadines) with CBDC project index 3 from the BIS working paper's [5] latest dataset as of July 2022. Countries with index 3 correspond to live CBDC. In contrast, index 2 corresponds to ongoing or completed pilot, 1 corresponds to public research studies, and 0 corresponds to no announced project [20][5].

3.2. Exploratory Data Analysis

Visualisation techniques were employed to comprehend better the interrelationships between the data's attributes and spot patterns. Furthermore, EDA paints a picture of the dataset as a whole, examines it prior to any hypotheses being made, identifies outliers or unusual occurrences, and unearths intriguing correlations among features. All things considered, EDA significantly enhances an analyst's fundamental comprehension of several factors. The figure below (Fig. 5) shows the relationship between two variables using the Pearson correlation coefficient [22]; this quantifies how closely two variables are related linearly. Its worth is between -1 and 1, depending on the following: A correlation of -1 implies a negative linear relationship when comparing two variables. No linear relationship exists between two variables if the value is 0. A correlation coefficient of 1 shows a strong positive linear relationship between two variables. For a given pair of variables, the strength of their association is indicated by how far their correlation coefficient deviates from zero. In the figure below (Fig. 5), the correlation between “GovernmentEffectiveness” and “Innovation_Score” is 0.90, which means there's a substantial positive correlation between them. It indicates that If a country's government can deliver high-quality public services and sound policies consistently, its citizens will be more inclined to be creative and entrepreneurial.

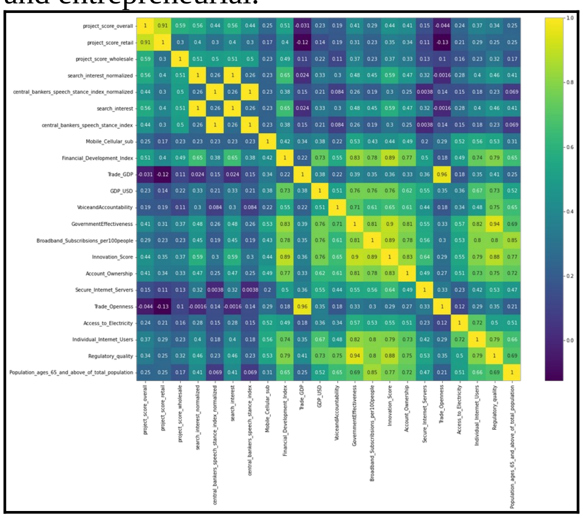

Fig. 5. Correlation Matrix of the dataset

Moreover, The figure below (Fig.6) shows that countries with higher CBDCPI tend to have high Government Effectiveness and Innovation scores, which supports the strong correlation between those two variables in Figure (Fig. 5).

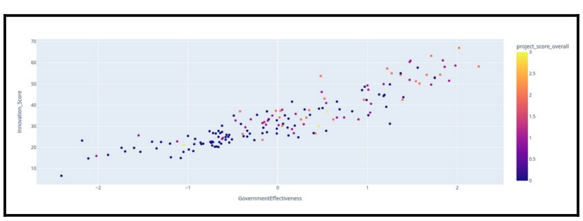

Fig. 6. Impact of “GovernmentEffectiveness” and “Innovation_Score” on the Overall CBDCPI.

Furthermore, the figure below (Fig. 7) shows that more economically advanced regions having CBDCPI 2 and 1 have an immense need for creative methods of wholesale settlement. It supports the strong positive correlation between “Financial_Development_Index” and “Innovation_Score” in the figure(Fig.5), which is 0.89.

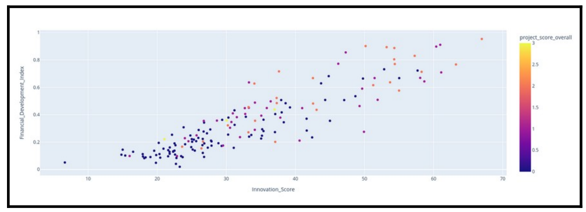

Fig. 7. Impact of “Financial_Development_Index” and “Innovation_Score” on the Overall CBDCPI.

3.3. Data Preparation

Data preparation or cleaning is vital. However, it takes a plethora of time, and the least enjoyable component of data science, as insufficient or low-quality data, can damage the veracity of insights or lead to false conclusions. Careful data preparation facilitates limiting errors and faults and preparing data for testing and implementing ML models.As shown in the figure (Fig. 3), there are a few variables with missing values,such-as“Innovation_Score”-and-“Account_Owners-hip”, which have more than 40 missing values.

Firstly, rows with a specific number of missing values were removed. Then, a regression model was used to predict the missing values of continuous features. The figure below (Fig. 8.) shows a code snippet where the Linear regression model was applied to predict missing values of the “Innovation_Score” column. The advantage of using a machine-learning algorithm to fill in missing values is that it outperforms other traditional approaches. Also, it considers the values and outliers column's correlation with others.

Filling up missing values of Innovation score column with machine learning

```
[ ] df_innovation_score = df.drop(['ISO2','country_name','project_score_overall','project_score_retail',

[ ] test_data_innovation_score = df_innovation_score[df_innovation_score['Innovation_Score'].isnull()]

[ ] test_data_innovation_score[['search_interest','central_bankers_speech_stance_index','Mobile_Cellular

    /usr/local/lib/python3.7/dist-packages/pandas/core/frame.py:3641: SettingWithCopyWarning:
    A value is trying to be set on a copy of a slice from a DataFrame.
    Try using .loc[row_indexer,col_indexer] = value instead

    See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
      self[k1] = value[k2]

[ ] df_innovation_score.dropna(inplace=True)

[ ] xtrain_innovation_score = df_innovation_score.drop('Innovation_Score',axis=1)

[ ] ytrain_innovation_score = df_innovation_score['Innovation_Score']

[ ] from sklearn.linear_model import LinearRegression
    lr_IS = LinearRegression()

[ ] lr_IS.fit(xtrain_innovation_score,ytrain_innovation_score)

    LinearRegression()

[ ] xtest_innovation_score = test_data_innovation_score[['search_interest','central_bankers_speech_stanc

[ ] ypred_innovation_score = lr_IS.predict(xtest_innovation_score)

[ ] ypred_innovation_score
```

Fig. 8. A Code snippet predicting missing values of the "Innovation_Score" column with machine learning.

3.4. Random Forest Classifier

In the vast landscape of classification algorithms that is data science, the Random Forest Classifier tops the hierarchy.

A random forest is a grouping of several different decision trees. Collective intelligence is harnessed in a random forest. Collectively, a vast proportion of essentially nonlinear models (trees) perform more effectively than the sum of their parts.

3.5. XGBoost Classifier

XGBoost implements the stochastic gradient boosting machine learning approach efficiently. It's a method that uses a group of decision trees that fixes faults in existing trees. The model is improved by adding trees. XGBoost performs well on imbalanced datasets. In many complex machine learning scenarios, the stochastic gradient boosting (or tree boosting) method performs admirably. Some classification benchmarks show that tree boosting outperforms its competitors [23].

4. RESULTS AND DISCUSSION

In [5], univariate and multivariate ordered probit regression were used to find a correlation between CBDC project index and other features considering CBDC project index as the target variable. However, in [20], they conceptualize this as a classification issue, wherein they are tasked with predicting the CBDCPI from independent features.

4.1. Overall CBDC Project Index

Before proceeding with the model implementation phase, the meaning of the overall CBDC project index should be explained briefly. According to [20], within the dataset presented in [5], there are two sub-indices: the retail CBDC project index and the wholesale CBDC project index. Wholesale CBDCPI is intended for financial institutions holding reserve deposits with a central bank. In contrast, retail CBDCPI seeks to replace cash and issue for the general public and the retailers. The maximum of these two sub-indices is a country's overall CBDC project index. For instance, if a country's retail CBDC project index is 1 and the wholesale CBDC project index is 2, then that country's overall CBDC project index will be 2.

Since the CBDC project index values are categorical, a Random forest classification model was constructed for its prediction [20]. To construct the model, we first collected data on 162 countries using the methods described in Section 6.3; we narrowed the available variables down to 17. The original set of 24 variables was narrowed down to 17, after which dependent and independent variables were established. Then, we created a training set and a test set with those variables. With random state=42, the method would then perform a random sampling with a probability of 42. All of the other settings were kept at their default values. Algorithmically, bootstrap sampling would partition data and produce fresh variables for each tree. To reach a conclusion, the algorithm would undergo a process of training and validation of all relevant variables. The output would be the conclusion reached by the majority vote, as trees produce conclusions [24]. Furthermore, another model was trained using the XGBoost classifier, where all parameters were kept default. Finally, after training both models on the training set and predictions were performed on the testing set, accuracy scores were obtained using actual and predicted values. The accuracy score of both models is presented in Table 1. It shows the accuracy of the random forest classifier on the testing set is 83%. It is higher than the accuracy obtained in [20], which is 77% and 68% on the testing set of aggregated data.

Classifier	Train	Test
Random Forest	1.0	0.83
XGBoost	1.0	0.80

Table 1. Accuracy score of the classifiers taking Overall CBDCPI as the target variable.

The top 10 features retrieved by Random forest to better comprehend a country's aspects that motivate it towards CBDC development are shown in the following figure (Fig.9). Search interest turned out to be the most important feature of our random forest model, followed by financial development index and Mobile cellular subscriptions.

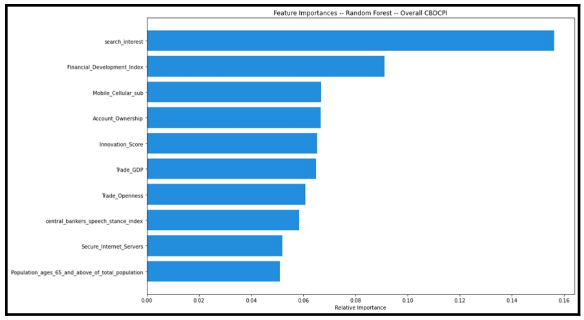

Fig. 9. Top 10 features of overall CBDCPI using Random forest.

The XGBoost classifier model's top 10 retrieved features are displayed in Fig. 10. Similarly, search interest was the most consequential factor in this model, followed by the central bank speech index and the degree to which markets were open to foreign commerce or trade openness.

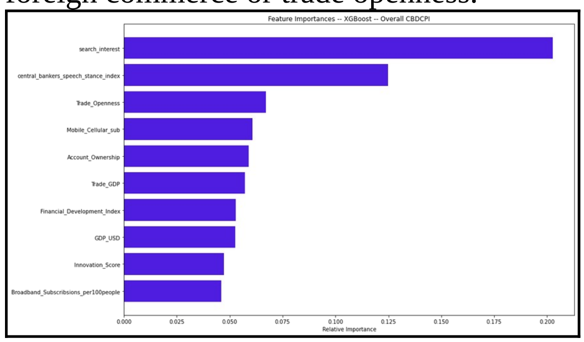

Fig. 10. Top 10 features of overall CBDCPI using XGBoost.

4.2. Retail CBDC Project Index

To predict a country's retail CBDC project index, two models have been implemented where the retail CBDC project index is used as the objective variable, in contrast to the model implementation described in Section 7.1. So, we have developed two additional models with the retail CBDC project index as the target variable rather than merely concentrating on a country's overall CBDC project index. The wholesale CBDC project index was also used in Section 7.3 to train two additional machine-learning models. In light of this, a new research frontier has been established.

The results of the accuracy of random forest and XGBoost are presented in Table 2, with the retail CBDC project index serving as the dependent variable. While the testing set only comprises two data points, the training set for each model contains eight different data points. The random state has been changed to 42, and all other parameters have been left at the default values.

Classifier	Train	Test
Random Forest	1.0	0.85
XGBoost	1.0	0.82

Table 2. Accuracy score of the classifiers taking Retail CBDCPI as the target variable.

The top 10 features determined by random forest that motivate to work towards retail CBDC are displayed in the figure (Fig. 11). Search interest ranked first, followed by the financial development index and trade openness.

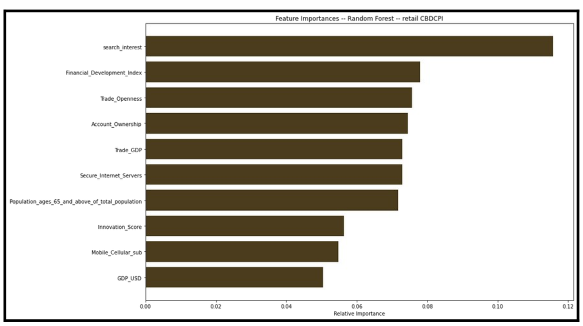

Fig.11. Top 10 features of retail CBDCPI using Random Forest.

4.3. Wholesale CBDC Project Index

Two more models have been deployed, with the wholesale CBDC project index as the dependent variable, as mentioned in subsection 7.2. Table 3 displays the model accuracy, which is the best of any model used in subsections 7.1 and 7.2.

Classifier	Train	Test
Random Forest	1.0	0.91
XGBoost	1.0	0.94

Table 3. Accuracy score of the classifiers taking Wholesale CBDCPI as the target variable.

Important features are retrieved using the random forest and XGBoost classifier models to identify probable drivers to implement wholesale CBDC since the models built using the wholesale CBDC project index provide higher accuracy.

The top 10 features determined by random forest are displayed in the figure (Fig. 12). Search interest ranked first, followed by the financial development index and the innovation score.

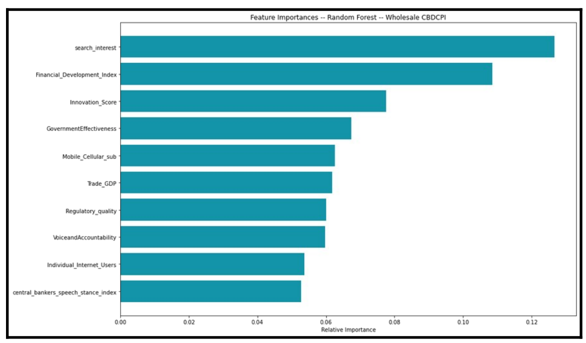

Fig. 12. Top 10 features of Wholesale CBDCPI using Random forest.

The XGBoost classifier's top 10 features are shown in (Fig. 13). Search interest is also the most important feature in this model, followed by the innovation score and the central banks' speech stance index.

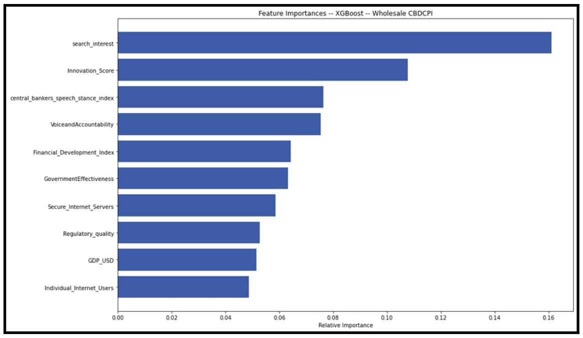

Fig. 13. Top 10 features of Wholesale CBDCPI using XGBoost.

5. CONCLUSION

The Central Bank of Malaysia (BNM) is continually doing research that will lead to the issuance of CBDC in Malaysia. This is happening even though Malaysia has no plans to do so in the near future. This study has leveraged machine learning techniques to extract the most important drivers that will instantiate the CBDC research in Malaysia. In all models created above, search interest turned out to be the most important factor, followed by the financial development index, innovation score, and trade openness. Search interest indicates public interest in digital currency, mostly a currency backed by sovereign entities and central banks' initiatives to implement CBDC [5]. In a similar vein, with the general public's best interests in mind, Bank Negara Malaysia is concentrating its efforts on the study and development of CBDC, which would play an essential role in the nation's payment infrastructure and bring Malaysia to a position of financial stability.

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