Migration Letters

Volume: 21, No: S8 (2024), pp. 1406-1417

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Machine Learning Techniques For Assessing Economic Factors Affecting Foreign Direct Investment Trends In Pakistan

Alamgir [1], Ubaid Ullah [2], Abdur Rehman[3], Ammara Nawaz Cheema[4], Mohammad Saleh Bataineh[5a,b] Zahid Iqbal*[6]

Abstract

The present research explores the complex realm of foreign direct investment (FDI) in Pakistan by analyzing FDI trends from 1997 to 2021 using sophisticated Machine Learning (ML) techniques including K Nearest Neighbors (KNN), Support Vector Regression (SVR), and Random Forest (RF). The research analyzes the effects of economic variables like trade openness, interest rate and rate of inflation on FDI inflows and evaluates the effectiveness of these cutting-edge machine-learning techniques, employing a rich tapestry of data from the World Bank, State Bank of Pakistan, [1]and World Development Indicators. A strong explanatory power is noticeable from the regression model's which explains approximately 59.7% of the dependent variable's fluctuation. Findings of the study reveal that KNN and RF happen to be the most dependable models as compared to SVR having lowest accuracy. The study also highlights how important these economic factors are in determining FDI trends. Further, the "Trade openness" (To) feature is found to be the most influential based on feature importance values. Therefore, in order to improve FDI in Pakistan, it is crucial that stakeholders pay attention to these insights.

Key Words: *Foreign Direct Investment; Machine Learning Models; Regression; Model Performance.*

Introduction

Due to rapid transportation and efficient communication systems, it now takes only a few hours to traverse from one country to another, and messages can be transmitted from one corner of the world to another within seconds. Similarly, businesses can relocate swiftly from one location to another without experiencing significant time delays. An exemplary instance of this business mobility is seen in foreign direct investment. The term "investment" denotes the accumulation of resources with the anticipation of obtaining future returns. In a broader

[1]Department of Statistics, University of Peshawar, ubaidullahyousafzai5683@gmail.com,
[2*]Department of Statistics, University of Peshawar, alamgir_khalil@uop.edu.pk,
[3]Department of Statistics, University of Peshawar, abdurrehmanshad@uop.edu.pk
[4*]Department of Mathematics, Air University, Islamabad, Pakistan; ammara.cheema@au.edu.pk; ammara.au@gmail.com
[5a]University of Sharjah; Mbataineh@sharjah.ac.ae
[5b]Yarmouk University; M.bataineh@yu.edu.jo
[6] Department of Statistics, Allama Iqbal Open University, Islamabad, Pakistan; zahid.iqbal@aiou.edu.pk
*Corresponding Author: Dr. Zahid Iqbal; zahid.iqbal@aiou.edu.pk

context, investment serves as the mechanism essential for financing the growth and development of an economy. Investments are commonly classified divided into two groups: investments in portfolios and foreign direct investment. Foreign direct investment is characterized as tangible investment and is described as a medium to long-term commitment [1]. The asset invested by citizens of a nation's economy in a foreign business that they effectively regulate is known as foreign direct investment [2].

Throughout history, FDI has been extremely important in the advancement of numerous host countries. It has contributed by enhancing their infrastructure, technical expertise, entrepreneurial capabilities, and financial resources, thereby positively impacting government revenue and foreign exchange [3].Foreign direct investment, or FDI, pertains to the flow of equity investment directly into the host country's economy. This involves reinvesting earnings, stock capital, and other types of capital. One kind of foreign investment known as a direct investment is one in which a citizen of one country exercises substantial control or influence over the operations of a company located in another country. The usual requirement is to hold 10% or more of the common stocks with voting rights used to establish the presence of a direct investment connection [4].

Pakistan's foreign direct investment experienced significant fluctuations in recent years. In 2019, FDI amounted to $2.23 billion, marking a substantial 28.61% increase from 2018. However, in 2020, FDI declined by 7.92% to $2.06 billion. The following year, in 2021, FDI rebounded to $2.15 billion, representing a 4.38% increase from the previous year. However, in 2022, FDI saw a sharp decline to $1.34 billion, marking a 37.63% decrease from the previous year [5]. These fluctuations indicate a degree of volatility in Pakistan's attractiveness to foreign investors and may reflect changes in the country's economic and political landscape during this period. In the fiscal year 2022-2023, Pakistan experienced fluctuations in foreign investment. Foreign private investment saw a decrease from 2,027.1 to 1,548.4, with direct investment also declining from 1,820.5 to 1,548.6. However, foreign public investment showed a significant decrease from 2,555.3 to 309.5 [6]. Portfolio investment also fluctuated, with equity securities showing a decrease and debt securities experiencing a significant increase. Overall, total foreign investment decreased from 1,857.8 to 522.3. These fluctuations indicate a mixed trend in foreign investment in Pakistan during this period, with both positive and negative changes in different sectors.

Overview of the Country's Profile

Location: Pakistan's central Asian location makes it an ideal starting point for exploring the abundant energy resources of Central Asia, the financially stable Gulf States, and the economically developed far Eastern countries. Pakistan is a market full of opportunities due to its strategic location, which borders China in the north, India on the east, Iran and Afghanistan on the west, and the Arabian Sea on the east. Total Area of Land: 796,096 Sq. km Land Boundaries: 7,266 km in total (China 580 km, India 2,240 km, Afghanistan 2,430 km, Iran 909 km).

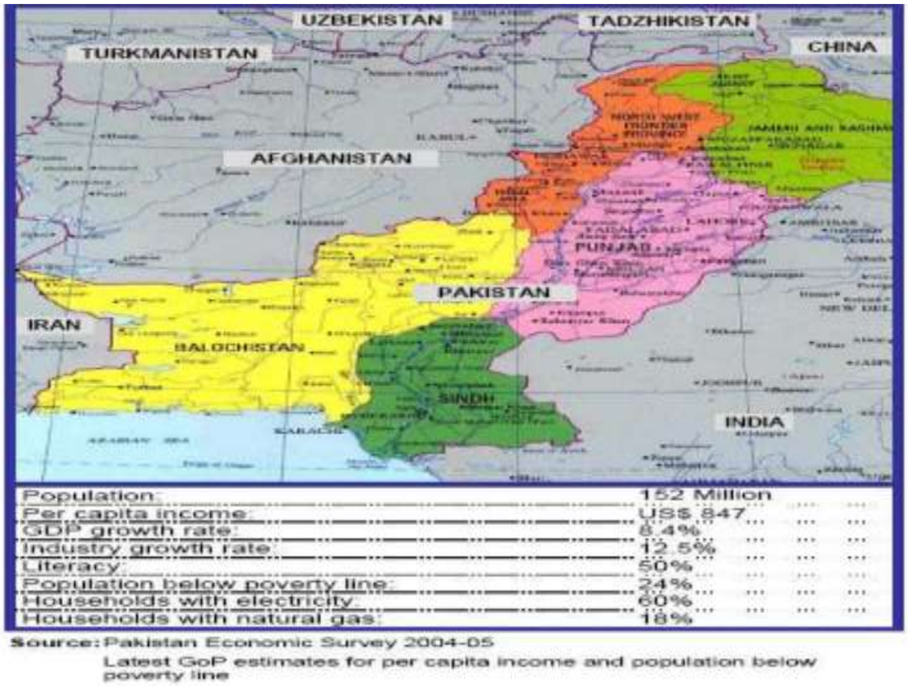

Figure #1 Pakistan's geographical location

The host nation's foreign direct investment (FDI) policy has a significant influence on foreign investment decisions. Any nation can enact embracing policies that promote international investment or levy different forms of restrictions on foreign involvement in its economy.

The evaluation has extensively shown the theorized connection between economic growth and trade openness [7–12]. Theoretically, trade deregulation and/or outside trade strategies, and consequently trade openness, have been argued to be beneficial to growth [13]. It's important to note that, despite the well-established theoretical link between trade openness, economic growth, and foreign direct investment (FDI), recent empirical research in developing nations has tended to focus on the individual effects of (i) trade openness and (ii) FDI on growth [14–18, 19–25]. Moreover, the Bhagwati hypothesis—that is, the relationship between foreign direct investment and trade openness (FDI)—is not expressly tested in empirical research examining both FDI and trade openness [26–32].

Waqas (2016) [33] employed the ARDL-ECM model to look into the influence of Foreign Direct Investment (FDI) on Pakistan's economic growth. Siddique et al. (2017) [34] highlighted a one-way causation, observing that economic growth leads to Foreign Direct Investment, subsequently influencing tangible assets and commerce. Anupama and Rupashree (2019) [35] employed ARIMA to predict the impact of FDI inflow and recommended that the government should devise policies and procedures to attract foreign investors to invest in various sectors, thereby fostering positive economic growth. FDI's impact on environmental emissions was examined by Demena, & Afesorgbor (2020) [36] using evidence from a meta-analysis. Tiwari et al. (2022) [37] looked into how the growth of the stock market drove the use of renewable energy: Is it possible trade openness, economic development, and foreign direct investment have an impact on Asian economies?

The current study intends to look at the effect of economic factors like trade openness, inflation rate, interest rate, exchange rate, and tax revenues on FDI inflows, and our study also contributes to the literature by predicting FDI using ML techniques like SVR, RF, and KNN; identifying key features impacting FDI.

The subsequent sections of this article are put together as follows:

The research methodology is explicated in Section 2 as well as sections 3 and 4 present the research results along with discussions, findings and conclusions, respectively.

2 MATERIAL AND METHODS

2.1 Data source

This section deals with the project method and procedure used in this study. This study is descriptive and quantitative in nature. The study's data was gathered from secondary sources such as World Bank [38], World development Indicators [39], State bank of Pakistan [6], from the year 1997 to 2021 and the results were analyzed using R and Python. Different Machine Learning methods have been utilized for data analysis. A succinct overview of these methods

2.2k-nearest neighbor

A basic machine-learning technique that may be utilized to solve issues with both classification and regression is the KNN approach. When used to regression, KNN simply calculates an object's property value as the mean of its k-nearest neighbors. Remarkably, studies [40-46] show that KNN finds extensive application in calculating forest characteristics with diverse sources of remote sensing data. Three key factors need to be decided upon in order to implement KNN: the number of neighbors (K), the distance measure to be used, and the weights to be assigned to the closest neighbors. In the case of unaltered anticipation factors, the i^{th}member of the target set element's KNN prediction is

$$\bar{y}_i = \frac{1}{w_i}\sum_{j=1}^{k} w_{ij}\, y_j^i,$$

Examine a situation in which the collection of response variable observations corresponding to k reference set members is represented by the notation $\{y_i,\ j = 1, 2... k\}$. These elements are selected according to how close they are, measured by a certain distance measure, d, to the feature space's ith element with the target set. Furthermore, in this instance, w_{ij}denotes the weight given to the j^{th} nearest neighbor.

$$w_i = \sum_{j=1}^{k} w_{ij}$$

The optimal value for k is user-determined and dependent on the properties of the data. According to Kozma (2008) [47], a greater k tends to introduce more bias, making the predictions less exact, whereas a lesser k may result in increased variance, making the model less stable. Distance-weighted KNN assigns a weight to each of the k neighbors based on how far away they are from a reference unit, with closer neighbors receiving a higher weight.

$$w = \frac{1}{d(x_{q\,,}x_i)},$$

The target and reference units in this case are represented by x_q and $x_i$respectively, while the distance between them is indicated by d. There are several ways to calculate the closeness between neighbors. Options encompassing Chebychev, city-block (Manhattan), squared Euclidean, and Euclidean distances are available in Statistica program. The most widely used of these is the basic mathematical distance in space with many dimensions can be referred to as the Euclidean distance. (Statistica 2010) [48].

$$D(x, p) = \sqrt{(x - p)^2}$$

The squared Euclidean method squares the delineation between the reference and desired units, giving items that are closer or more similar with an increased weight:

$$D(x, p) = (x - p)^2$$

Absolute value distances are considered in the Manhattan distance measure. Nevertheless, Statistica 2010 points out that because individual massive deviations (outliers) are not squared, their influence is minimized.

$$D(x, p) = (x - p)$$

D is the delineation between the reference and desired units in each equation, where the source unit is “p” and the desired outcome unit is “x” [49-50] other distance measures, including Manhattan [51] weighted Euclidean [52] and non-weighted Euclidean [53] have been applied in several studies to evaluate different items. Therefore, K-Nearest Neighbors (KNN) leverages the idea that comparable cases in a feature space are likely to display similar outcomes to provide predictions or classifications based on the similarity of data points.

2.3 Support vector machines, Regression

The Support vector machines (SVM) algorithm is a set of methods for both regression and classification that has its roots in statistical learning theory [54]. Vapnik's (1998) [55] generalized portrait algorithm is extended nonlinearly by it. In general, support vector machines (SVMs) focus on drawing the class border and converting the independent variable-created input space through a nonlinear transformation enabled by a kernel function. Sigmoid, polynomial, linear, and radial basis function (RBF) which are the kernels that are numerous frequently utilized in SVM applications [56-57]

SVMs find the best linear separator, or hyper plane, within the resultant high-dimensional space to optimize the distance between two classes. By increasing the margin, the risk of over fitting is successfully mitigated and the solution is made more broadly [54]. Three important factors affect how well Support Vector Regression performs: 1) the parameter known as capacity (C) represents a compromise between the most significant amount and the complexity of the model of deviations that are allowed to exceed C. 2) The training data is fitted using the ε-insensitive zone, and its width is determined by epsilon (ε). 3) According to Cortez and Morais (2007) [56], gamma (γ) is a kernel function parameter that affects SVR performance. Remarkably, the value of epsilon is crucial in deciding how many support vectors (SVs) are utilized to build the regression function. Regression estimates are less complicated and training periods are shortened when a larger epsilon results in fewer chosen SVs [47-48] [58].

2.3 Random forest

The techniques used in [59], introduction of classification and regression trees (CART), are expanded upon by RF. Regression-type scenarios, in which the objective is to forecast an ongoing dependent variable, as well as categorization challenges, in which the goal is to forecast a variable that is dependent which is categorical, may both be solved with RF because of its versatility. An assortment of basic trees, or subsets of explanatory features, interacts in the RF by casting votes to provide replies. After that, an estimate for the dependent variable is obtained by averaging or combining the replies. The variables and data are randomly picked using an iterative sacheting bootstrap investigation procedure to build a regression tree forest. For an RF, the variability of mean square is computed as

$$\text{Random forest predictions} = \frac{1}{\text{k}}\sum_{\text{k}=1}^{\text{k}} \text{k}^{\text{th}} \text{ tree response}$$

When applied to a Random Forest (RF), the index "k" loops over every single tree in the forest. All of these individual trees' projections are averaged to determine the RF's predictions.

$$\text{Mean error} = (\text{observed} - \text{tree response})^2$$

The number of trees (terminal nodes) in all regression trees where a target sample and a reference sample share a terminal node is subtracted to get the distinction between the base unit and desired units. For a more thorough justification, see Breiman (2001).Random Forest' implementation success depends on decision tree regularization and stopping settings. The maximum numbers of trees that can be erected in the forest and the number of randomly selected variables (k predictors or independent variables in each node for predicting dependent values) in each node are two of the decision tree model's parameters. (Statistica 2010). In this article, we rely on the Random Forests' regression feature. The user can designate how many trees are in a forest. Assume M represents the total number of trees in the forest.
The way the random forest approach functions is as follows:
1.Select several subsets (xi) at random from a given dataset (X).
2. Construct M decision trees using sampled data.
3. Compute the decision trees' average vote total.
4. As the ultimate approximation, return the average.

3 Results and discussion

According to Ragazzi, 1973 [60], the money that citizens of a nation invest in a foreign company that they effectively control is known as foreign direct investment. Three popular non-parametric machine-learning methods were used in this research endeavor to evaluate foreign direct investment (FDI). The major objective of this study was to assess and contrast these three prevalent machine-learning techniques (KNN, SVR and RF) and to focus on different economic factors like trade openness, inflation rate, interest rate, exchange rate, tax revenues on FDI inflows.

Table 1. Descriptive Statistics for Economic variables

Variable(s)	N	Minimum	Maximum	Mean	Std. Deviation
Foreign direct investment	25	.3755	3.6683	1.106147	.9022084
Exchange rate	25	41.1115	162.9063	85.474925	35.2103613
Trade openness	25	.2470	0.3685	.304250	.0354254
Inflation	25	2.9000	17.0000	7.604000	3.6961106
Tax revenue	25	11.2	16.0	13.924	1.1352
Interest rate	25	5.24	18.00	10.4528	3.26703

Table1 presents descriptive statistics for key economic variables, including Foreign Direct Investment, Exchange Rate, Trade Openness, Inflation, Tax Revenue, and Interest Rate.

Table 2 Analysis of Variance and Model summary

Model	Sum of Squares	Degree of freedom	Mean Square	F	Sig.	R	R Square
Regression	11.669	5	2.334	5.637	0.002	.773	.597
Residual	7.866	19	0.414				
Total	19.536	24					

The regression model's overall statistical significance (F=5.637, p=.002) according to the ANOVA findings suggests that the explanatory factors together have a substantial effect on the response variable and hence the regression model's explanatory variables are responsible for around 59.7% of the variability in the response variable. This suggests that a significant amount of the variation in the response variable is captured by the model, offering a strong basis for future projections and choices based on the model's output.

3.1 Implementation of machine-learning techniques and their results

The differences between a model's projected values and the actual values are estimated by the Root Mean Square Error, or RMSE. It functions as a common indicator to evaluate regression models' efficacy. Different types of regression models include Random Forest, K-Nearest Neighbors (KNN), and Support Vector Regression (SVR).When comparing these models on the basis of RMSE, It's crucial to remember that each model's performance may differ according to the particular dataset and challenge at hand. Table 3 presents performance of the three ML algorithms.

Table 3 Root means square errors of ML models

S.NO	Models	Root mean square error
1	K nearest neighbors	0.7207
2	Random forest	0.7617
3	Support vector regression	0.8611

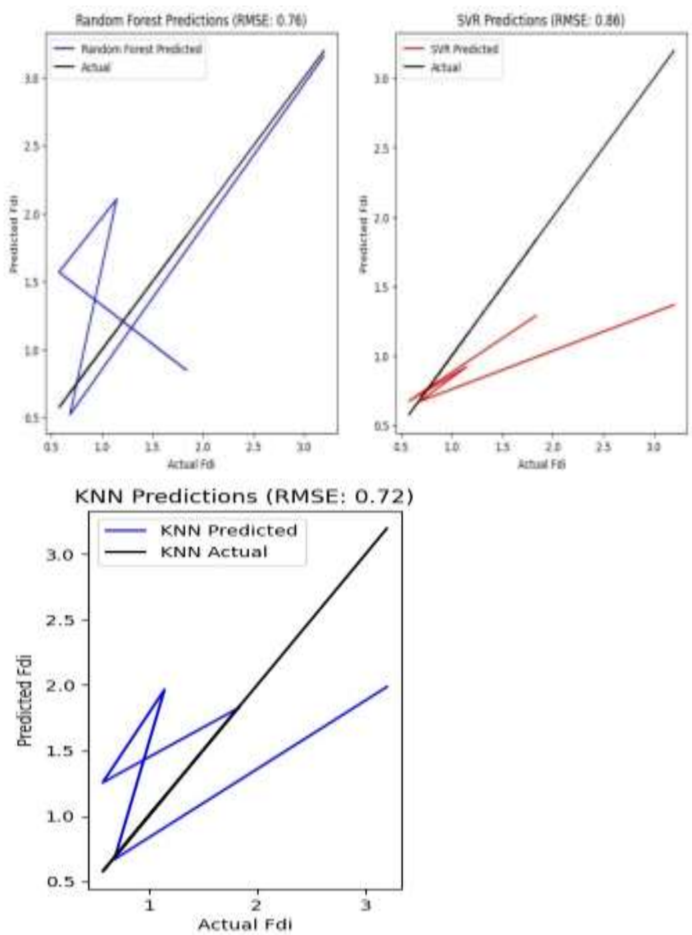

Figure 2: Prediction of Foreign Direct Investment using ML models

Based on the RMSE values provided, the KNN model appears to be the most accurate for this particular dataset, followed by Random Forest, with Support Vector Regression performing the least accurately.

Table 4: Model comparison based on MAE, MARD and MSE

S.NO	Model	MAE	MARD	MSE
1	Random forest	0.6267	0.6686	0.6285
2	Support vector regression	0.5421	0.2507	0.7416

Table 4 presents comparison of various models on the basis of Mean Absolute Error (MAE) and Mean Absolute Relative Difference (MARD) (measures used to assess regression models' effectiveness). Based on the results, the SVR model appears to have better performance in terms of MAE and MSE, while the Random Forest model has a lower MARD. These metrics provide different perspectives on the models' predictive accuracy and error.

Table 5: SVM(R) Kernel selection based on RMSE

Kernel types	RMSE for linear	RMSE for RBF	RMSE for Polynomial
Accuracy	0.8538	0.8611	0.7124

Table 5 provides RMSE results for various kernels used in SVM (R). Based on the provided RMSE values, the Polynomial kernel type demonstrates the most outstanding demonstration of performance in terms, followed by the RBF kernel type, with the linear kernel type performing the least accurately.

Table 6: Features importance for predictions

Feature	Trade openness	Inflation rate	Tax revenue	Interest rate	Exchange rate
Importance	0.5293	0.2452	0.1228	0.0456	0.0308

The feature importance values provided in Table 6 represent the relative importance of each feature in a predictive model. An elevated level of significance suggests that the feature or variable has a stronger influence on the model's predictions, while a lower importance value indicates a relatively weaker influence and hence the feature labeled " Trade openness " has the highest importance value (0.5293), suggesting that it is the aspect of the model's predictions with most influence.

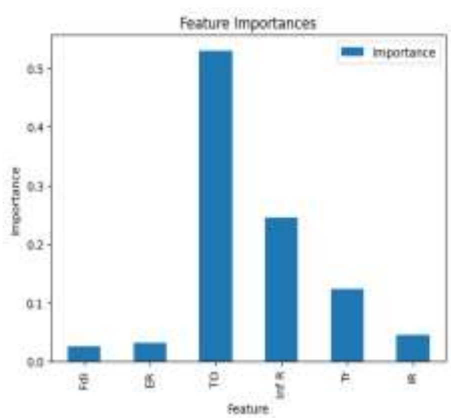

FIGURE 3: Bar plot of Feature Importance

Conclusion

A foreign direct investment (FDI) is the acquisition of an asset in another nation that affords the individual who purchases it direct control over the asset. Machine learning algorithms—KNN, SVR, and RF in particular—were used to evaluate foreign direct investment (FDI) in Pakistan. Data from 1997 to 2021-were drawn from secondary sources for the study, such as, World Bank, and World Development Indicators. In addition to focusing on several economic parameters including trade openness, inflation rate, interest rate, currency rate, and tax revenues on FDI inflows, the major goal was to analyze and evaluate the effectiveness of these machine-learning techniques.

The article found that the independent factors explained around 59.7% of the variability in the dependent variable showing a significant impact of the regression model on the dependent variable. Moreover, the analysis showed that Support Vector Regression performed the least accurately, while Random Forest and K Nearest Neighbors seemed to be the best accurate models for this dataset. The Mean Absolute Relative Difference (MARD) and Mean Absolute Error (MAE) metrics were used to assess the performance of the ML models. SVR performed better in terms of MAE and MSE, whereas Random Forest had a lower MARD.

As far as SVR model is concerned, the polynomial kernel type performed the most exemplary linguistically of prediction accuracy, subsequently, it was found that the RBF kernel type. The "Trade Openness" feature received the highest feature importance value, indicating that it had the most influence on the model's predictions. The performance of various machine-learning techniques and the discovered economic aspects should be taken into account by investors and government officials in Pakistan when making assessments on foreign direct investment.

References

1. Khattak, N. U. R. (2012). The contribution of education to economic growth: evidence from Pakistan.
2. Ragazzi, G. (1973). Theories of the Determinants of Direct Foreign Investment (Théorie des facteurs qui déterminent l'investissement étranger direct) (Teorías de los determinantes de la inversión extranjera directa). Staff Papers-International Monetary Fund, 471-498.
3. Lall, S., & Narula, R. (2004). Foreign direct investment and its role in economic development: do we need a new agenda?. The european journal of development research, 16, 447-464.
4. Lipsey, R. E., Feenstra, R. C., Hahn, C. H., & Hatsopoulos, G. N. (1999). The role of foreign direct investment in international capital flows. In International capital flows (pp. 307-362). University of Chicago Press
5. Macro-trends, the long term perspective. (https://www.macrotrends.net/)
6. State bank of Pakistan report. Retrieved from (https://www.sbp.org.pk/)
7. Grossman,G. M., & Helpman, E. (1990). Comparative advantage and long-run growth.American Economic Review,80, 796–815.
8. Grossman, G. M., & Helpman, E. (1991).Innovations and growth in the global economy.Cambridge: MIT Press.
9. Rivera-Batiz, L.A., & Romer, P.M. (1991). International trade with endogenous technological change. European Economic Review, 35, 971–1001.
10. Ben-David, D., & Loewy, M. (2000). Knowledge dissemination, capital accumulation, trade, and endogenous growth. Oxford Economic Papers, 52, 637–650.
11. Ben-David, D., & Loewy, M. (2003). Trade and the neoclassical growth model. Journal of Economic Integration, 18, 1–16.
12. Perera-Tallo, F. (2003). Growth due to globalization. International Economic Review, 44, 651–676.
13. Krueger, A. O. (1998). Why trade liberalization is good for growth. The Economic Journal, 108, 1513–1522.
14. Mani, U. H., & Afzal, M. N. I. (2012). Effect of trade liberalization on economic growth of developing countries: A case of Bangladesh economy. Journal of Business, Economics and Finance, 1(2), 37–44.
15. Asiedu, M. K. (2013). Trade liberalization and growth: The Ghanaian experience. Journal of Economics and Sustainable Development, 4(5), 125–135.
16. Hassen, S., Anis, O., Taha, Z., & Yosra, S. (2013). Trade openness and economic growth: The case of Tunisia. International Journal of Advances in Management and Economics, 2(2), 24–32.
17. Sakyi, D., Villaverde, J., & Maza, A. (2014). Trade openness, income levels, and economic growth: The case of developing countries, 1970–2009.The Journal of International Trade &Economic Development, 23(8), 1–23.
18. Karam,F., & Zaki, C. (2015). Trade volume and economic growth in the MENA region: Goods or services? Economic Modeling, 45, 22–37.
19. Adams, S. (2009). Foreign direct investment, domestic investment, and economic growth in sub-Saharan Africa. Journal of Policy Modeling, 31(6), 939–949.

20. Gudaro, A. M., Chhapra, I. U., & Sheikh, S. A. (2010). Impact of foreign direct investment on economic growth: A case study of Pakistan. Journal of Management and Social Sciences, 6(2), 84–92.
21. Onakoya, A. B. (2012). Foreign direct investments and economic growth in Nigeria: A disaggregated sector analysis. Journal of Economics and Sustainable Development, 3(10), 66–75.
22. Yalta, A. Y. (2013). Revisiting the FDI-led growth hypothesis: The case of China. Economic Modeling, 31, 335–343.
23. Hong, L. (2014). Does and how does FDI promote the economic growth? Evidence from dynamic panel data of prefecture city in China. IERI Procedia, 6, 57–62.
24. Nistor, P. (2014). FDI and economic growth, the case of Romania. Procedia Economics and Finance, 15, 577–582.
25. Temiz, D., & Gokmen, A. (2014). FDI inflow as an international business operation by MNCs and economic growth: An empirical study on Turkey. International Business Review, 23, 145–154.
26. Liu, X., Burridge, P., & Sinclair, P. J. N. (2002). Relationships between economic growth, foreign direct investment and trade: Evidence from China. Applied Economics, 34(11), 1433–1440.
27. OtengAbayie,E.F.,&Frimpong,J.M.(2006).Boundstestingapproachtocointegration:Anexamination of FDI, trade, and growth relationships. American Journal of Applied Sciences, 3(11), 2079–2085.
28. Naveed, A., & Shabbir, G. (2006). Trade openness, FDI and economic growth: A panel study. Pakistan Economic and Social Review, 44(1), 137–154.
29. Constant, N. Z. S., & Yaoxing, Y. (2010). The relationship between foreign direct investment, trade openness and growth in Cote d'Ivoire. International Journal of Business and Management, 5(7), 99–107.
30. Adelowokan, O. A., & Maku, A. O. (2013). Trade openness, foreign investment and economic growth in Nigeria: A long-run analysis .European Journal of Globalization and Development Research, 7(1), 446–458.
31. Soi, N., Koskei, I., Buigut, K., & Kibert, J. (2013). Impact of openness, foreign direct investment, gross capital formation on economic growth in Kenya. Journal of Economics and Sustainable Development, 4(14), 130–135.
32. Belloumi, M. (2014). The relationship between trade, FDI and economic growth in Tunisia: An application of the autoregressive distributed lag model. Economic Systems, 38, 269–287.
33. Javaid, W. 2016. Impact of foreign direct investment on economic growth of Pakistan-An ARDL-ECM approach. Thesis submitted to Sodertorn University, Stockholm, Sweden.
34. Siddique, H.M.A., R. Ansar, M.M. Naeem and S. Yaqoob. 2017. Impact of FDI on Economic Growth: Evidence from Pakistan. Bulletin of Business and Economics, 6 (3): 111-116.
35. Anupama, G. and Rupashree R. 2019. Forecast of Foreign Direct Investment Inflow (2019- 2023) with reference to Indian Economy. International Journal of Research in Engineering, IT and Social Sciences, 09 (4): 22-26.
36. Demena, B. A., & Afesorgbor, S. K. (2020). The effect of FDI on environmental emissions: Evidence from a meta-analysis. Energy Policy, 138, 111192.
37. Tiwari, A. K., Nasreen, S., & Anwar, M. A. (2022). Impact of equity market development on renewable energy consumption: Do the role of FDI, trade openness and economic growth matter in Asian economies? Journal of Cleaner Production, 334, 130244.
38. World Bank report. Retrieved from https://www.worldbank.org/en/home on dated 20.02.2022
39. World Bank Database. Retrieved FROM https://databank.worldbank.org/source/ on dated 20.02.2022
40. FRANCO-LOPEZ, H., EK, A.R. and BAUER, M.E., 2001, Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbor's method. Remote Sensing of Environment, 77, pp. 251–274.
41. KATILA, M. and TOMPPO, E., 2001, Selecting estimation parameters for the Finnish multisource national forest inventory. Remote Sensing of Environment, 76, pp. 16–32.
42. OHMANN, J.L. and GREGORY, M.J., 2002, Predictive mapping of forest composition and structure with direct gradient analysis and nearest neighbor imputation in coastal Oregon, U.S.A. Canadian Journal of Forest Research, 32, pp. 725–741.
43. MAKELA, H. and PEKKARINEN, A., 2004, Estimation of forest stands volumes by Landsat TM imagery and stand-level field-inventory data. Forest Ecology and Management, 196, pp. 245–255.

44. FINLEY, A.O., MCROBERT, R.E. and EK, A.R., 2006, applying an efficient k-nearest neighbor search to forest attribute imputation. Forest Science, 52, pp. 130–135.
45. MCROBERT, R., TOMPPO, E., FINLEY, A. and HEIKKINEN, J., 2007, Estimating aerial means and variances of forest attributes using the k-nearest neighbors technique and satellite imagery. Remote Sensing of Environment, 111, pp. 466–480.
46. TATJANA, K., SUPPAN, F. and SCHNEIDER, W., 2007, the impact of relative radiometric calibration on the accuracy of kNN-predictions of forest attributes. Remote Sensing of Environment, 110, pp. 431–437.
47. KOZMA, L., 2008, k nearest neighbor algorithm (kNN). Helsinki University of Technology, Special course in computer and information science. Available online at: www.lkozma. net/knn2.pdf
48. STATISTICA, 2010, Electronic text book, Stat Soft Inc. Available online at: www.Statsoft.com
49. FRANCO-LOPEZ, H., EK, A.R. and BAUER, M.E., 2001, Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbors method. Remote Sensing of Environment, 77, pp. 251–274.
50. REESE, H., NILSSON, M., SANDSTRÖM, P. and OLSSON, H., 2002, Applications using estimates of forest parameters derived from satellite and forest inventory data. Computers and Electronics in Agriculture, 37, pp. 37–55.
51. SIRONEN, S., KANGAS, A. and MALTAMO, M., 2010, Comparison of different non-parametric growth imputation methods in the presence of correlated observations. Forestry, 83, pp. 39–51.
52. ESKELSON, B.N.I., HAILEMARIAM, T. and BARRETT, T.M., 2009, estimating current forest attributes from paneled inventory data using plot-level imputation: a study from the Pacific Northwest. Forest Science, 55, pp. 64–71.
53. MCROBERT, R.E., 2009, Diagnostic tools for nearest neighbors techniques when used with satellite imagery. Remote Sensing of Environment, 113, pp. 489–499.
54. WALTON, J.T., 2008, Sub pixel urban land cover estimation: comparing cubist, random forests, and support vector regression. Photogrammetric Engineering & Remote Sensing, 74, pp. 1213–1222.
55. VAPNIK, V., 1998, Statistical Learning Theory (New York: John Wiley & Sons).
56. CORTEZ, P. and MORAIS, A., 2007, A data mining approach to predict forest fires using meteorological data. In Proceedings of the EPIA 2007 – Portuguese Conference on Artificial Intelligence, December 2007, J. Neves, M.F. Santos and J.M. Machado (Eds.), Guimarães, Portugal (Heidelberg: Springer), pp. 512–523.
57. DURBHA, S.S., KING, R.L. and YOUNAN, N.H., 2007, Support vector machines regression for retrieval of leaf area index from multiangle imaging spectroradiometer. Remote Sensing of Environment, 107, pp. 348–361.
58. WANG, X., YANG, C., QIN, B. and GUI, W., 2005, Parameter selection of support vector regression based on hybrid optimization algorithm and its application. Journal of Control Theory and Applications, 4, pp. 371–376.
59. BREIMAN, L., 2001, Random forests. Machine Learning, 45, pp. 5–32.
60. Ragazzi, G. (1973). Theories of the Determinants of Direct Foreign Investment (Théorie des facteurs qui déterminent l'investissement étranger direct) (Teorías de los determinantes de la inversión extranjera directa). Staff Papers-International Monetary Fund, 471-498.