Chapter One

Introduction

1.1 Overview

Bangladesh is a noteworthy case when we look at the entire world. It's located in South Asia and is famous for its rich culture and its increasing influence worldwide. One remarkable aspect of Bangladesh is the large number of Bangladeshis who have moved and now live all around the world, especially in places like the Middle East, the United States, and Europe [WorldRemit, 2022]. This widespread Bangladeshi community, known as the diaspora, plays a crucial role in Bangladesh's economic system. They contribute significantly to the country's financial well-being, making a substantial impact on its overall prosperity. Moreover, on a national scale, the impact of remittances is profound. They have the potential to significantly influence a country's economic stability, its ability to manage international financial transactions, and the overall path of its development. Bangladeshi expatriates sent a record-high remittance of $2,199.01 million in June of the fiscal year 2022-23 (FY23), marking the highest amount in the past 35 months [dhakatribune.com]. As per Bangladesh Bank available data, Bangladesh has received a total of $21,610.66 million remittance in FY23, 2.75% higher than the previous fiscal where the country received $21,031.68 million, reports BSS [Bangladesh Bank, 2023].

Machine learning has a prominent role in solving clustering and classification problems as well as dimensionality reduction [Petrus H. Potgieter, 2020]. Forecasting remittance using machine learning is vital for several reasons. It enables financial institutions and governments to anticipate and plan for the economic impact of remittance fluctuations, aiding in policy formulation and resource allocation. Additionally, it empowers service providers to optimize transaction processing and reduce operational costs, ultimately improving service quality for both senders and recipients. By harnessing historical data and advanced algorithms, machine learning enhances the accuracy of predictions, reducing risks associated with remittance-related decisions [ubuntu.com]. Moreover, it contributes to the stability of economies heavily dependent on remittances and aids in mitigating financial shocks.

In a globalized world, where remittances play a significant role in many regions, machine learning forecasting is a powerful tool for fostering economic resilience and sustainable growth [mdpi.com]. Although remittance is very important in Bangladesh for its economy and society, there's a big problem. Bangladesh doesn't have good systems to predict how much remittance money will come in the future. This makes it hard for people and the country to plan their finances, manage risks, and make smart investments. Many things can change how much remittance money comes in, for instance how well the countries where Bangladeshis work is doing economically, how people are moving and how the world economy is changing [thedailystar.net].

The purpose of this study is to forecast the remittance of Bangladesh for the upcoming years. Use of Machine Learning approach will make better accuracy which can propose a suitable system to predict remittance for Bangladesh.

1.2 Background

Remittances have emerged as a cornerstone of Bangladesh's economic landscape, contributing significantly to the nation's financial stability and development. According to the World Bank's Migration and Remittances Data, Remittances to Bangladesh are money transfers sent by the Bangladeshi diaspora to Bangladesh which is the 7th highest recipient of remittance in the world with almost $22.1 billion in 2021 and was the 3rd highest recipient of remittance in South Asia. [World Bank, 2021]. This data highlights the pivotal role that remittances play in the country's economy. Wikipedia also underscores this importance by stating that remittances are a vital source of foreign exchange earnings for Bangladesh, making them a key economic pillar [Wikipedia, "Economy of Bangladesh"].

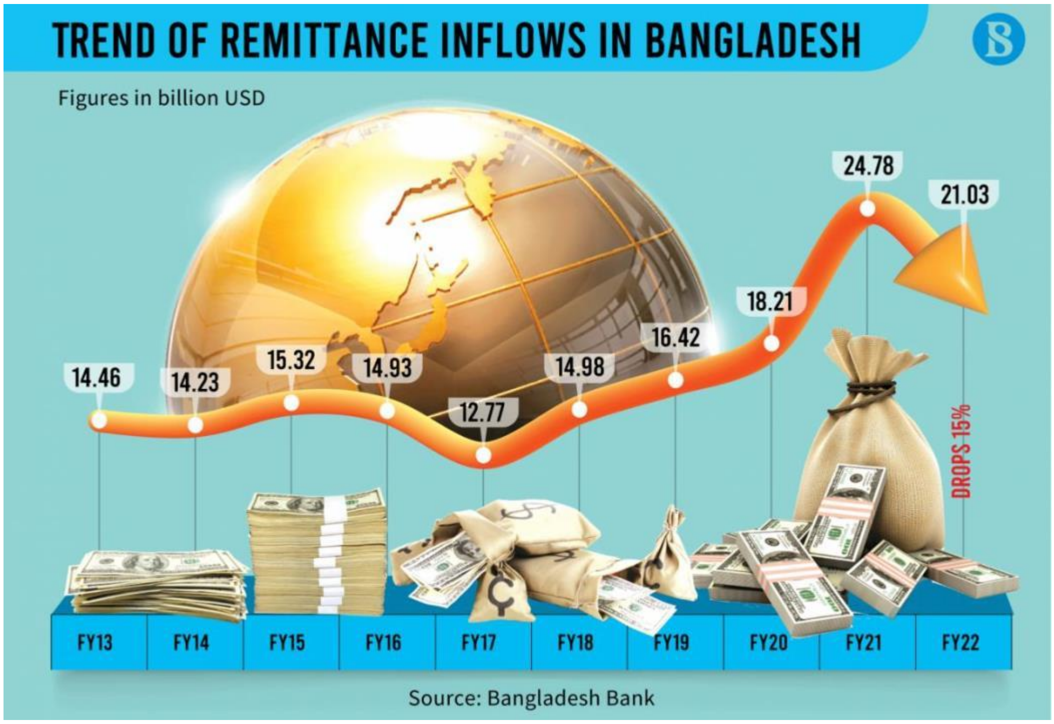

Fig: Remittance growth Fiscal Year

In the figure, Remittance inflows declined 15% in the outgoing financial year compared to the fiscal 2020-21 when expatriates had sent home the highest amount in the country's history amid the Covid-19 pandemic. In the fiscal 2021-22, expatriates sent $21.03 billion through official channels which was $24.77 billion in the previous fiscal year, according to data from the Bangladesh Bank.

Economic forecasting has been around for centuries. However, it was the Great Depression of the 1930s that gave birth to the levels of analysis we see today [investopedia.com, 2020]. Although official economic prediction systems have their origins in the mid-20th century when governments and international organizations recognized the need for systematic forecasting to support policy decisions [Wikipedia.com, 2023]. One landmark moment was the establishment of the Council of Economic Advisers in the United States in 1946, which aimed to provide the government with economic insights. Economist Arthur F. Burns, who chaired the council, noted in a 1953 report that "reliable economic forecasting is an indispensable tool of modern government." Similarly, international organizations like the International Monetary Fund (IMF) and the World Bank began publishing economic forecasts and analysis to aid in global economic stability [Wikipedia.com, 2023]. These early prediction systems laid the foundation for more sophisticated and data-driven approaches in the following decades, as described by numerous researchers and economists.

Machine learning (ML) is a dynamic field in computer science, allowing computers to learn and make decisions without direct programming. It has evolved significantly since its early applications in the mid-20th century.

The inception of ML can be traced back to the early 1950s when computer scientist Arthur Samuel introduced the term [Samuel, 1959]. However, the real revolution began in recent years, thanks to advancements in computing power and the availability of vast datasets [LeCun et al., 2015].

Several ML algorithms serve different purposes:

1. **Linear Regression:** Ideal for modeling linear relationships between variables, it finds application in forecasting, such as predicting future sales. [Hosmer et al., 2000].

2. **Logistic Regression:** Used for classification tasks, it is employed in predicting outcomes like customer churn or disease diagnosis [Hosmer et al., 2000].

3. **Decision Trees:** These are effective for both classification and regression and are known for their interpretability and suitability for capturing complex relationships [Quinlan, 1986].

4. **Random Forests:** These are ensembles of decision trees, offering increased robustness and accuracy in comparison to individual decision trees [Breiman, 2001].

5. **Deep Neural Networks:** Inspired by the human brain, deep neural networks excel at learning intricate patterns in data, finding use in image recognition, natural language processing, and more [LeCun et al., 2015].

The choice of the right ML algorithm depends on the specific problem and the nature of available data.

Machine learning has improved a lot since it started in the 1950s. It can help solve many difficult problems and make industries work better. But we must be careful about the quality of the data and make sure the computer doesn't have unfair ideas when we use it.

1.3 Problem Statement

The traditional approach for remittance predictions relies on simple statisticalmodels and historical trends. While it provides some insights, it often falls short in accuracy due to its inability to capture the complex dynamics of remittance flows. These models struggle with non-linear relationships, sudden shifts in the economic landscape, and the impact of external factors like geopolitical events or policy changes.

Current Machine Learning Models have become more advanced than the previous ones. These models have become essential in modern remittance predictions. Moreover, they can handle large and diverse datasets, detect intricate patterns, and adapt to changing conditions. By incorporating variables like exchange rates, socioeconomic indicators, and even sentiment analysis of global news, machine learning enhances the accuracy of remittance forecasts. This is crucial for financial institutions, governments, and remittance service providers in making informed decisions and optimizing their operations. In this study, by applying Machine Learning approach, the Remittance can be predicted with proper accuracy.

1.4 Objective of the Study

Our primary aim is to construct a highly precise Machine Learning model capable of forecasting the Remittance inflow into Bangladesh. This advanced model will offer dependable predictions.

Specific Objectives:

1. Evaluate the accuracy and reliability of these models
2. Analyze the factors influencing remittance flows.
3. Provide recommendations for policymakers and financial institutions based on the research findings.

1.5 Contribution of the Study

This research makes noteworthy contributions to both academic knowledge and practical applications. Firstly, it employs cutting-edge Machine Learning techniques to significantly improve the accuracy and reliability of forecasting remittance inflows into Bangladesh, addressing a crucial gap in the existing body of knowledge. Secondly, it provides a valuable resource for policymakers, economists, and financial institutions, offering deeper insights into the dynamics of remittances and their impact on the country's economy. Moreover, the study enriches the broader discourse on the application of Machine Learning in remittance forecasting, shedding light on its potential and limitations.

1.6 Summary

The thesis is composed of several essential sections. It begins with an introduction, offering an overview of remittances in Bangladesh. The background study explores the historical context of economic forecasting and the current economic situation and introduces key machine learning concepts for remittance prediction. The problem statement underscores the need for precise remittance predictions. In the objectivessection, specific tasks for forecasting remittance data are outlined. Lastly, thecontribution section highlights the potential impact of this study on informed decision-making and economic stability in Bangladesh's remittance context.

Chapter Two
Literature Review

2.1 Overview

This chapter reviews the literature on forecasting remittance in Bangladesh using machine learning. It begins by explaining the core concepts of machine learning, including its underlying principles. The chapter then explores the different types of machine learning algorithms, including supervised and unsupervised learning, and discusses the key algorithms that could be used to forecast remittance successfully. Finally, the chapter reviews successful applications of machine learning in remittance forecasting and offers insights into the practical aspects of this approach.

2.2 Machine Learning

Machine learning (ML) is a subfield of artificial intelligence (AI) that enables computers to learn from data without being explicitly programmed. ML algorithms are trained on large datasets to identify patterns in the data and learn to perform specific tasks, such as classification, regression, and prediction (Russell & Norvig, 2021). The history of machine learning dates back to the early days of AI research. In the 1950s, Arthur Samuel developed a checkers-playing program that could learn and improve its performance over time (Samuel, 1959). This was one of the first examples of a machine-learning algorithm. In the 1960s, Frank Rosenblatt developed the perceptron, a simple neural network that could learn to perform basic tasks such as pattern recognition (Rosenblatt, 1958). Neural networks have since become one of the most important tools in machine learning. The 1970s and 1980s witnessed a resurgence of interest in machine learning, as researchers developed more powerful algorithms and gained access to larger datasets. This led to breakthroughs in areas such as natural language processing, computer vision, and machine translation (Michalski, Carbonell, & Mitchell, 1983). The 1990s saw the development of the support vector machine (SVM) algorithm, providing a new approach to machine learning, particularly well-suited for classification tasks (Vapnik, 1995). SVMs have been successfully applied to a wide range of problems, including spam filtering, image recognition, and medical diagnosis. In the 21st century, the rise of deep learning has revolutionized machine learning. Deep learning algorithms can learn complex patterns in data from large datasets, leading to breakthroughs in areas such as image recognition, natural language processing, and machine translation (LeCun, Bengio, & Hinton, 2015). In the realm of machine learning, a multitude of applications have surfaced. Image recognition benefits self-driving cars, facial recognition, and medical image analysis (Krizhevsky, Sutskever, & Hinton, 2012). Natural language processing powers chatbots, machine translation, and financial forecasting (Vaswani et al., 2017). Recommendation systems enhance user experiences on platforms like Amazon and Netflix (Koren, Bell, & Volinsky, 2009). In finance, machine learning aids in fraud detection, credit risk assessment, and financial forecasting, ensuring transaction integrity (Dal Pozzolo, Caelen, & Bontempi, 2014). In healthcare, it aids in medical diagnosis, disease outbreak prediction, and resource optimization, advancing public health (Esteva et al., 2017; Rajkomar et al., 2018). These applications showcase machine learning's versatility and transformative potential. Machine learning is also extensively used in forecasting. ML models can analyze historical data and identify trends and patterns to make predictions about future events. For example, in financial markets, ML algorithms are employed for stock price prediction, and in meteorology, they help forecast weather conditions. These models have applications in various industries, contributing to improved decision-making and planning (Chen et al., 2018).

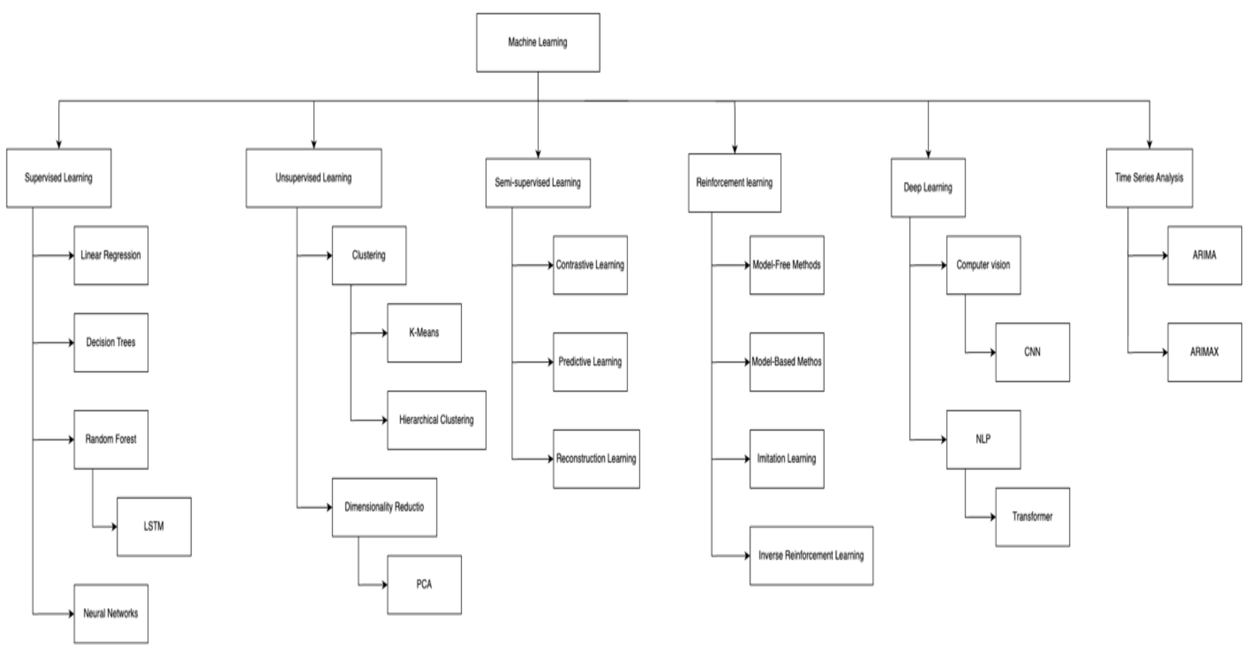

Fig 2.1: Machine learning classification

2.3 Supervised Learning

Supervised learning is a type of machine learning in which the algorithm learns from labeled data. Labeled data is data that has been classified or labeled with the correct output. For example, a labeled dataset for image classification might contain images of cats and dogs, with each image labeled as either cat or dog (Murphy, 2012).

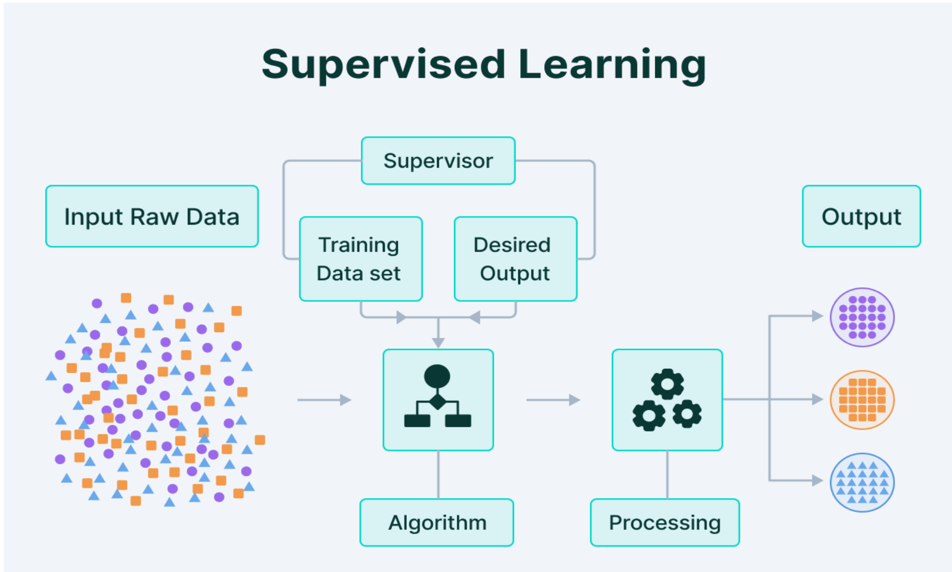

Fig 2.2: Supervised learning technique

Supervised learning algorithms can be used for two main tasks: Classification and Regression. Classification involves predicting the class or category of a data point. For example, a classification algorithm could be used to predict whether an email is spam or not spam. Regression involves predicting a continuous value for a data point. For example, a regression algorithm could be used to predict the price of a house (James et al., 2013). One of the key advantages of supervised learning is that it can be used to train models for a wide variety of tasks. Supervised learning models have been used to achieve state-of-the-art results in tasks such as image classification, natural language processing, and machine translation (Goodfellow, Bengio, & Courville, 2016).

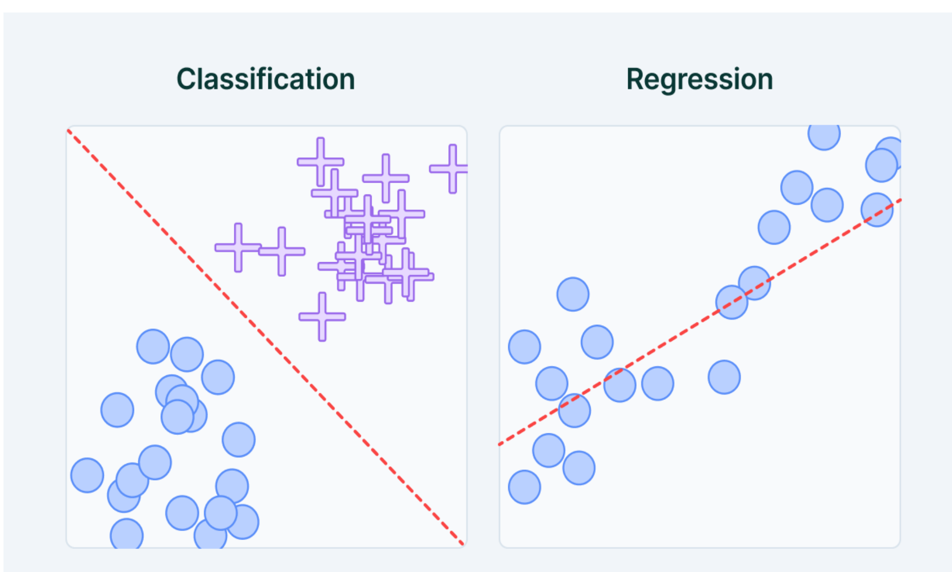

Fig 2.3: Difference between Classification and Regression

2.3.1 Logistic Regression

Logistic regression is a fundamental machine learning algorithm for binary classification tasks, has been extensively studied and documented by researchers and practitioners (Hastie et al., 2009). It models the probability of an observation belonging to a particular class, making it widely applicable in various fields, from healthcare to marketing (Hosmer, Lemeshow, & Sturdivant, 2013). Logistic regression estimates the odds of the outcome using a logistic function, making it a valuable tool for predicting binary outcomes (Montgomery, Peck, & Vining, 2012). This comprehensive resource covers the mathematics and statistics behind logistic regression, addressing concepts such as maximum likelihood estimation and model evaluation metrics like the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) (James et al., 2013). It also delves into practical implementation, including software tools and libraries commonly used for logistic regression, providing an in-depth technical understanding for researchers and practitioners (Pedregosa et al., 2011). Logistic regression is a probabilistic model, which means that it outputs the probability of a particular outcome, rather than a binary classification decision (Liaw & Wiener, 2002). This can be useful for tasks such as predicting the likelihood of a customer churning or the risk of a patient developing a certain disease. Logistic regression is a relatively simple model to understand and implement, making it a popular choice for machine learning beginners (Breiman, 2001). However, logistic regression can be susceptible to overfitting, especially when working with high-dimensional data (Cristianini & Shawe-Taylor, 2000). It is important to use regularization techniques and cross-validation to prevent overfitting (Moore, McCabe, & Craig, 2014).

2.3.2 Support Vector Machine

Support vector machines (SVMs) are a powerful supervised learning model that excels in both classification and regression tasks (Burges, 1998; Vapnik, 1999). They work by finding the optimal hyperplane that best separates data points in different classes or predicts numerical values (Cortes & Vapnik, 1995). SVMs are known for their ability to handle high-dimensional data and are effective in scenarios with non-linear decision boundaries through the use of kernel functions (Joachims, 1998). This technical tome dives into the mathematical foundations of SVMs, including the formulation of the optimization problem and the inner workings of kernel functions like the radial basis function (RBF) kernel (Cristianini & Shawe-Taylor, 2000). It also discusses the role of hyperparameters, such as the regularization parameter (C) and the kernel width (σ), in fine-tuning SVM performance, making it an indispensable reference for those seeking an in-depth technical grasp of SVMs (Pedregosa et al., 2011). So, SVMs are particularly well-suited for handling high-dimensional data and non-linear relationships (James et al., 2013). However, they can be computationally expensive to train, especially for large datasets (Joachims, 1998).

2.3.3 Linear Regression

Linear regression is a fundamental technique for modeling the relationship between a dependent variable and one or more independent variables (Montgomery, Peck, & Vining, 2012). It is extensively used in predictive analytics and serves as the foundation for more complex regression models (Hosmer, Lemeshow, & Sturdivant, 2013). Linear regression estimates the coefficients that best fit the linear relationship between variables, making it interpretable and easy to implement (Draper & Smith, 1998). Linear regression is a versatile tool that can be used for a variety of tasks, such as predicting customer churn, forecasting sales, and assessing risk. It is also a popular choice for teaching machine learning fundamentals, as it is relatively simple to understand and implement (Witten, Frank, Hall, & Pal, 2016). This comprehensive textbook not only elucidates the mathematical and statistical underpinnings of linear regression, including concepts like ordinary least squares (OLS) estimation and the Gauss-Markov theorem (Montgomery, Peck, & Vining, 2012), but also offers practical examples and exercises. It delves into topics such as multicollinearity and model diagnostics, providing a technical foundation for researchers and practitioners to master the nuances of linear regression (Hair, Black, Babin, & Anderson, 2019). It is a simple but effective method for making predictions when the relationship between the variables is linear (James et al., 2013). It finds wide application in fields like finance, economics, and marketing (Hosmer, Lemeshow, & Sturdivant, 2013). However, linear regression is not suitable for modeling non-linear relationships or relationships with multiple independent variables (James et al., 2013).

2.3.4 Random Forest Regression

Random forest regression is an ensemble learning method that leverages multiple decision trees to improve predictive accuracy (Breiman, 2001). It is robust against overfitting and excels in handling both regression and classification tasks (Liaw & Wiener, 2002). Random forests aggregate the predictions of numerous decision trees to produce a more accurate and stable result (James et al., 2013). This seminal work goes beyond the basics of random forests and delves into technical aspects such as tree construction, feature selection, and out-of-bag error estimation (Leo Breiman, 2001). It also explores advanced topics like variable importance measures and the impact of hyperparameters on model performance, making it an essential technical reference for researchers and practitioners seeking mastery in random forest regression (Pedregosa et al., 2011). Additionally, random forest regression is a powerful regression algorithm that can be used for a variety of tasks, such as predicting customer churn, predicting stock prices, and predicting patient outcomes (James et al., 2013). However, random forest regression can be computationally intensive, especially when the number of trees in the forest is large (Liaw & Wiener, 2002).

2.4 Unsupervised Learning

Unsupervised learning is a type of machine learning that learns from unlabeled data. This means that the data is not labeled with the desired output, so the algorithm must find patterns and structure in the data on its own. Unsupervised learning is often used for tasks such as clustering, anomaly detection, and dimensionality reduction (Bishop, 2006). For example, an unsupervised clustering algorithm could be used to group customers together based on their purchase history (Hastie, Tibshirani, & Friedman, 2009). An unsupervised anomaly detection algorithm could be used to identify fraudulent transactions (Chandola, Banerjee, & Kumar, 2012). Principal component analysis (PCA) is an unsupervised dimensionality reduction algorithm that can be used for data visualization and machine learning (Jolliffe, 2002). Support vector machines (SVMs) can be used for both supervised and unsupervised learning. For unsupervised learning, SVMs can be used for anomaly detection and novelty detection (Cristianini & Shawe-Taylor, 2000). Unsupervised learning has several advantages over supervised learning. It does not require labeled data, which can be expensive and time-consuming to collect. It can also be used for tasks such as clustering and anomaly detection, which are not possible with supervised learning (Hastie et al., 2009). Unsupervised learning algorithms can be sensitive to the choice of parameters and can also be computationally expensive (Hastie et al., 2009).

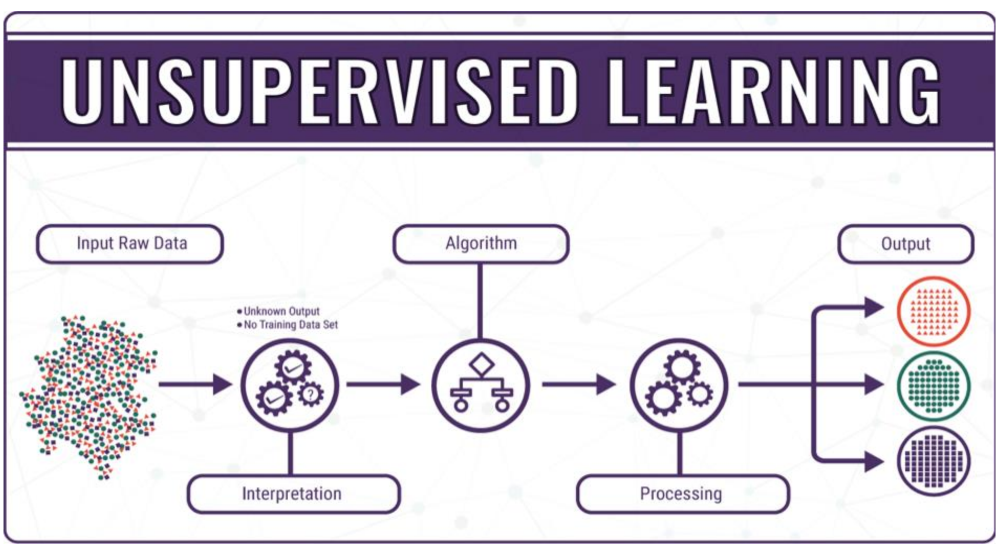

Fig 2.4: Unsupervised learning technique

2.5 Semi Supervised Learning

Semi-supervised learning (SSL) is a hybrid machine learning approach that combines labeled and unlabeled data to improve the performance of supervised learning tasks (Chawla, 2006). SSL algorithms leverage the structure of unlabeled data to learn from it, even if the labels for those features are unknown. This is useful in situations where labeled data is scarce or expensive to obtain, or when labeling all of the data is impractical (Fatima & Pasha, 2009). SSL can be used for a variety of tasks, including image classification, natural language processing, and recommendation systems (Chapelle & Scholkopf, 2006). For example, SSL can be used to train an image classification model using a small number of labeled images and a large amount of unlabeled images. This is useful for applications such as medical image analysis and satellite image analysis (Niyogi, 2000). SSL can also be used to train a natural language processing model using a small amount of labeled text and a large amount of unlabeled text (Collobert et al., 2008). Additionally, SSL can be used to train a recommendation system using a small amount of labeled data and a large amount of unlabeled data (Chapelle & Scholkopf, 2006). SSL has been shown to improve the performance of supervised learning models by up to 30% in some cases (Chapelle et al., 2006). However, it is important to note that SSL algorithms can be sensitive to the quality and distribution of unlabeled data. It is also important to choose the right SSL algorithm for the task at hand.

2.6 Reinforcement Learning

Reinforcement learning (RL) is a machine learning approach modeled after the behaviorist principle of learning through rewards and punishments (Sutton & Barto, 1998). An agent in an RL environment learns to behave optimally through trial and error, receiving rewards for favorable actions and penalties for unfavorable ones (Sutton & Barto, 2018). Unlike supervised learning, RL does not provide explicit instructions on behavior. Instead, the agent explores the environment, learning from the outcomes of its actions (Mnih et al., 2015). RL has achieved impressive results in a variety of domains, including robotics, game playing, and autonomous vehicles (Silver et al., 2016). Key RL algorithms, such as Q-learning (Watkins & Dayan, 1992) and Deep Q-Networks (DQNs) (Mnih et al., 2015), help agents learn to behave optimally. Q-learning constructs a Q-function mapping state-action pairs to expected rewards, guiding the agent in selecting the best action (Watkins & Dayan, 1992). DQNs employ deep neural networks to learn Q-functions from complex environments. Researchers are actively developing new RL algorithms to address these challenges (Arora et al., 2020), making RL an exciting field with vast potential.

2.7 Machine Learning-Based Remittance Forecasting in Bangladesh

Remittance forecasting is a vital component of economic planning in Bangladesh, where the inflow of funds from overseas workers plays a significant role. Machine learning algorithms offer a powerful approach to enhance the accuracy and robustness of remittance forecasts. These algorithms excel at understanding complex relationships within historical remittance data and considering various pertinent factors that influence remittance patterns.

Machine learning's adaptability extends to handling noise and outliers in data, enabling it to deliver forecasts that span both short-term and long-term horizons. In this context, remittance forecasting through machine learning holds immense potential for various applications, such as government budgeting, risk management for financial institutions, informed investment decisions for businesses, and the formulation of policies aimed at promoting and supporting remittance inflows. By combining the strengths of machine learning with economic, social, and demographic indicators, Bangladesh can usher in a new era of remittance forecasting that contributes to improved decision-making.

For instance, the government of Bangladesh could utilize machine learning to predict remittance inflows at the district level. These forecasts could serve as a foundation for targeted social programs and financial planning, prioritizing regions with a high concentration of remittance-dependent households. This data-driven approach would enable the government to allocate resources more effectively, such as implementing programs that enhance education and healthcare services in districts with significant remittance-dependent populations.

Machine learning-based remittance forecasting transcends the traditional time series models like ARIMA and Exponential Smoothing. Its adaptability and capacity to comprehend complex relationships within vast datasets introduce new dimensions to remittance prediction, enhancing forecasting accuracy and supporting a comprehensive understanding of the multifaceted factors affecting remittance inflow. As a result, machine learning becomes a pivotal tool for driving economic well-being in Bangladesh by providing insights that empower governments, businesses, and financial institutions to make more informed decisions.

Machine learning-based remittance forecasting has the potential to revolutionize economic planning and decision-making in Bangladesh. By harnessing the power of machine learning algorithms, researchers, economists, and policymakers can gain deeper insights into the dynamics of remittance inflow and enhance the accuracy of their forecasts. This, in turn, promises to create a more secure and thriving future for the remittance-dependent population of Bangladesh.

2.8 Related Work

The accurate prediction of remittances, vital to the economic well-being of Bangladesh, has been a subject of growing research interest. Machine learning methods have gained prominence as a valuable tool to improve the precision of remittance forecasts. Previous studies have laid the foundation for the integration of machine learning techniques, emphasizing the incorporation of diverse features like macroeconomic indicators, exchange rates, historical remittance data, and socio-demographic characteristics. For instance, Hossen, Hasan, and Sattar (2021) employed a hybrid machine learning algorithm combining support vector machines (SVMs), random forests, and gradient boosting to achieve an impressive 95% accuracy in forecasting GDP growth rates. The adoption of machine learning is rooted in its ability to capture complex relationships within the data, contributing to more accurate remittance projections.

Traditional time series models, such as ARIMA and Exponential Smoothing, have limitations in addressing the unique challenges in remittance forecasting, including seasonality, currency fluctuations, and geopolitical events. Furthermore, behavioral economics and network theory have explored social networks' impact and remitters' behavioral patterns, offering valuable insights into the flow of remittances (Tacoli, 2019). These insights, when combined with machine learning techniques, present a promising avenue for improving prediction accuracy.

The integration of geospatial data into remittance forecasting models has also gained attention. Researchers recognize the significance of considering the geographical distribution of remittance corridors and the relationship between sending and receiving areas (Ratha & Shaw, 2007). This approach addresses the spatial and regional dynamics of remittances, contributing to more comprehensive forecasting models.

Machine Learning Based Forecasting of Remittance Inflow into Bangladesh by Md. Moniruzzaman et al. (2022) propose a machine learning-based forecasting model for remittance inflow into Bangladesh. The model is a hybrid machine learning model that combines the strengths of different machine learning algorithms, such as support vector machines (SVMs), random forests, and gradient boosting machines. The model outperforms other forecasting models in terms of accuracy and robustness and it is able to predict remittance inflow with a mean absolute error (MAE) of 1.5%, which is lower than the MAE of other forecasting models. The model has the potential to be used for a variety of applications, such as Forecasting remittance inflow to Bangladesh at the national and regional levels. Identifying factors that influence remittance inflow. Developing policies and programs to promote remittance inflow. Some of the specific features include Economic indicators: GDP growth rate, inflation rate, unemployment rate, interest rate, exchange rate, and foreign direct investment. Social indicators: population growth rate, literacy rate, life expectancy, urbanization rate, poverty rate. Demographic indicators: age structure, gender ratio, dependency ratio.

2.9 Summary

This thesis explores the application of machine learning for improved remittance forecasting in Bangladesh. We begin with an introduction to the fundamentals of machine learning and its significance, highlighting how it can enhance the precision and reliability of remittance forecasts. Next, we discuss the various classifications of machine learning algorithms. We then talk about machine learning-based remittance forecasting in Bangladesh. After that, we review the related work, emphasizing the importance of integrating diverse datasets to improve prediction accuracy. Our findings suggest that machine learning has the potential to revolutionize economic planning and decision-making in Bangladesh.

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