# A Proposed Framework for Disease Prediction Using Machine Learning Techniques (FDPMLT)

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*Abstract - A lot of people are interested in how machine learning may be used in healthcare, as it could help with illness prediction and prevention. Disease Prediction using Machine Learning Techniques (FDMLT) is a new framework that aims to improve disease prediction models in terms of accuracy and efficiency. It is introduced in this study. To build reliable prediction models, the suggested framework makes use of a wide variety of machine learning algorithms, data pretreatment approaches, and feature engineering methodologies. In the first step of the framework, several healthcare datasets are thoroughly investigated. These datasets include clinical factors, genetic information, and patient records. After then, the data is painstakingly prepared for analysis by means of cleaning, normalisation, and imputation to guarantee the dataset's integrity and accuracy. In order to improve the model's predictive potential, feature engineering approaches are used to extract pertinent data and generate useful features.*

*Keywords - Disease, Prediction, Machine Learning, Fdmlt*

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## 1. INTRODUCTION

One area that has seen tremendous progress is illness prediction, which is part of a larger trend towards the integration of cutting-edge technology into the healthcare system. In this light, the Disease Prediction utilising Machine Learning Techniques (FDPMLT) framework stands out as a game-changing approach that might transform the way different medical illnesses are detected and predicted in their early stages. Developing efficient and reliable prediction models is becoming more and more important as the global burden of illnesses keeps rising. FDPMLT is an all-encompassing method that assesses large datasets including clinical history, environmental variables, genetic markers, and patient information by using machine learning algorithms. (Jeyalatha, S., & Sumbaly, R. 2015) We are excited to announce that this framework will bring about a new age of proactive healthcare by addressing the obstacles associated with old diagnostic procedures. In order to find complex connections and patterns in healthcare datasets, FDPMLT uses a combination of advanced machine learning methods and thorough data analytics. Machine learning offers a way to traverse the complicated terrain of medical data, which requires a change from traditional diagnostic approaches due to its sheer volume and complexity. (Sharma, V. 2015) The goal of FDPMLT is to improve the efficiency and accuracy of illness prediction by using algorithms that can adapt and learn from data. Decision trees, support vector machines, neural networks, and ensemble methods are just a few of the machine learning algorithms included in the framework. Each algorithm is designed to perform a unique set of tasks related to disease prediction, dictated by the dataset and the specifics of the disease in question. (Dhayanand, S. 2015)

When it comes to improving the model's prediction skills, FDPMLT also recognises the significance of feature extraction and selection. The framework's goal is to perfect the prediction process by giving due respect to pertinent elements; this way, the algorithm will only use the most relevant information when making decisions. Because healthcare providers need to understand the reasoning behind the predictions in order to make educated judgements, FDPMLT also stresses the need of being able to analyse and explain the results. The framework's incorporation of explainable AI approaches improves the forecasts' credibility and makes it easier to incorporate these predictions into clinical practice. (Rajeswari, P., & Reena, G. S. 2019)

With its extensive illness prediction capabilities, FDPMLT finds use in a wide variety of medical fields, including those dealing with infectious diseases, cancer, and chronic problems including diabetes and cardiovascular disorders. The framework's adaptability makes it a useful tool for public health professionals, who may use it to spot illness patterns early on and implement preventative measures. A paradigm change from

reactive to preventative medicine might be ushered in by FDPMLT's use of machine learning, which has the ability to radically alter healthcare delivery. (Tarmizi, N. D. A., et al. 2018)

## 1.1 Background

The use of technology is causing a revolutionary change in healthcare, especially in the area of illness prediction. Chronic and complicated illnesses are becoming more common as a result of changing lifestyles and expanding populations. Improving patient outcomes while decreasing the load on healthcare systems is made possible by early identification and aggressive management of illnesses. Clinical observations and historical data are commonly used in traditional illness prediction systems, however these approaches may not be as accurate or scalable as they seem. (Manimeglai, D. 2016)

New opportunities have arisen for healthcare providers with the rise of machine learning (ML) in the last several years. There is hope that machine learning approaches can improve the accuracy of illness forecasts by analysing large volumes of data, finding patterns, and making predictions. Gain useful insights into illness risk, progression, and treatment response using machine learning models that analyse electronic health records (EHRs) and include real-time data from wearable devices.

## 1.2 Overview of the Growing Significance of Disease Prediction

A game-changing innovation that uses cutting-edge tech to foresee and lessen health hazards on a community and individual level is the rising importance of disease prediction in healthcare. The development of AI, machine learning, and big data analytics has provided medical practitioners with cutting-edge resources for illness prediction and prevention.

Disease prediction relies on sifting through massive datasets that include a wide variety of health information, including EHRs, genetic data, lifestyle decisions, and environmental variables, to find trends and patterns. By analysing these datasets, we may identify any health problems early on, which in turn allows for proactive interventions and individualised treatment programmes. This preventative method lessens the financial burden of healthcare by enhancing patient outcomes and avoiding reactive interventions. (Rambhajani, M., et al. 2015)

The ability of machine learning algorithms to learn and adapt to new data is crucial for illness prediction. Predictive models are made more accurate and efficient by these algorithms because they can spot connections and trends that humans would miss. Predictive analytics, for instance, can use an individual's specific risk variables to foretell the

occurrence of chronic illnesses like diabetes or cardiovascular disease.

Additionally, public health programmes now greatly rely on illness prediction at the population level. The healthcare system is able to allocate resources more effectively and put in place more precise preventative measures in response to illness outbreaks that are predicted by analysing epidemiological data. Because of this, we have been able to respond more quickly to new health issues, such as pandemics, which has been a tremendous help.

## 1.3 The Role of Machine Learning in Healthcare

When it comes to healthcare, machine learning (ML) is making a huge impact, fixing old problems and making things better for patients, doctors, and the system as a whole. Utilising machine learning in healthcare is characterised by its capacity to sift through massive information, identify trends, and provide predictions; this, in turn, helps healthcare providers make better decisions and get better results. (Smith, A., & Johnson, B. 2018)

Machine learning has several uses in healthcare, but one of the most important is diagnosis. Machine learning algorithms are incredibly accurate when it comes to analysing medical pictures. This includes X-rays, MRIs, and CT scans. Algorithms like this learn from massive datasets and aid in the detection of abnormalities and subtle patterns that humans might miss. By improving both the speed and accuracy of diagnoses, this allows for the early discovery of illnesses and the prompt implementation of therapies.

When it comes to customising treatment regimens and forecasting patient outcomes, machine learning is a game-changer. Medical event likelihood and treatment response may be evaluated by ML algorithms through the analysis of electronic health records, genetic information, and other pertinent data. By optimising treatment techniques for specific patients, healthcare practitioners are able to give more personalised and effective care. Healthcare operational efficiency may be enhanced with the use of machine learning. Models based on predictive analytics can optimise the allocation of resources, anticipate the rates of patient admission, and detect any bottlenecks. Healthcare institutions are able to better manage their resources, decrease wait times, and improve overall service quality with this proactive strategy. (Gupta, S., & Sharma, P. 2019)

## 2. LITERATURE REVIEW

**Chen, Y., Li, Y., & Narayan, V. (2021)** heart disease prediction with an emphasis on feature engineering and ensemble learning. When it comes

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to boosting the accuracy and generalizability of predictions, their work emphasises the crucial impact of feature selection and model ensemble. This methodology shows a sophisticated grasp of the practical issues of using machine learning for illness prediction by tackling unbalanced datasets and having the model be interpretable. All of these frameworks add to the ever-changing field of healthcare machine learning, which highlights how important it is to take a methodical and coordinated approach if we want to use predictive modelling to its maximum capacity for patient care.

**Wang, L., Wang, Y., & Chen, Y. (2020)** When it comes to healthcare data, machine learning is crucial for managing and deriving insights from massive datasets, especially when their number and complexity keep on increasing. utilised machine learning to effectively forecast the onset of chronic illnesses through the utilisation of data extracted from electronic health records. Strong illness prediction models require a holistic approach, which their system emphasises by integrating feature selection, data preparation, and ensemble learning methods. Machine learning might greatly improve healthcare prevention and early diagnosis, according to the research, which would lead to better, more individualised treatment for patients.

**Patel, S., & Shah, M. (2019)** The revolutionary potential of using machine learning techniques to illness prediction has made it a hot topic in recent years. In order to accurately and early diagnose different illnesses, several research have investigated the integration of distinct machine learning techniques. Researchers have used methods including decision trees, neural networks, and support vector machines to sift through massive medical information. These algorithms prove that they can accurately detect patterns, pinpoint risk factors, and forecast the results of diseases. the efficacy of deep learning models in foretelling patient outcomes and trajectories using EHRs, establishing the groundwork for applying advanced machine learning methods to illness prediction systems.

**Zhang, W., & Wang, J. (2018)** Shovendra Sharma, MD It is time-consuming and expensive for someone who is sick right now to visit a doctor. Because the user's disease cannot be diagnosed, it might be challenging for them if they are not near physicians and hospitals. The patient may benefit from a more streamlined process if the aforementioned operation can be performed utilising automated software that reduces costs and saves time. Different Heart Disease Prediction Systems assess the patient's risk using data mining techniques. An online tool called Disease Predictor may diagnose a user's illness from their current set of symptoms. The Disease Prediction system has acquired data sets from a variety of websites that pertain to health. Using the symptoms provided, the user of condition Predictor can ascertain the probability of a condition. With the

proliferation of internet use, it's no surprise that people are perpetually interested in expanding their knowledge. People typically seek answers online when problems arise. When compared to the average person, healthcare facilities and doctors have far less internet connection. There are few choices available to persons who are sick.

**Khan, F., & Javaid, M. (2017)** The prevalence of chronic illnesses has increased to the point that they affect one-third of the population in every country. People with chronic diseases have it tough and pay a premium for healthcare. Medical professionals collect and analyse massive amounts of data on chronic diseases; data mining helps in early illness diagnosis. A diagnosis of a cardiovascular illness, diabetes, liver disease, Alzheimer's disease, or Parkinson's disease will set you back substantially. The medical and healthcare sectors have a significant difficulty when it comes to providing top-notch services to all patients, since only those with the means to pay may access them. There is a lot of healthcare data out there that isn't being reliably and efficiently mined to find out what the key is for good decision-making. To identify chronic illnesses at an early stage, the suggested framework makes use of data mining tools. Computers may be taught to provide better results by analysing examples or historical data; this technique is known as machine learning. Machine learning refers to the study of digital systems that acquire new skills via exposure to data and past experiences.

## 3. METHODOLOGY

The three information mining computations, such as the Decision tree classifier, Random forest classifier, and Naïve Bayes classifier, are used to carry out the disease expectation framework. Here is the depiction and operation of the calculations:

### 3.1 Decision Tree Classifier

Decision trees appear like trees when they're in use for grouping models. It learns a series of express on chance rules on highlight values (side effects in our case), which allows it to segment the dataset into progressively smaller groups, ultimately leading to the prediction of an objective value (illness). The decision nodes and the leaf nodes make up a decision tree.

Decision hub: Includes a minimum of two divisions. Every single one of the side effects is treated as a decision node in our newly presented study.

Although Decision Tree is most commonly used to address Order difficulties, it is a Regulated learning method that may be applied to characterization and relapse problems as well. In this tree-structured classifier, the nodes deal with the dataset's highlights, the branches with the decision rules, and the hubs of the leaves deal with the results.

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The Decision Hub and the Leaf Hub are the two nodes that make up a decision tree. Leaf nodes are the end result of decisions and do not include any further branches, while decision nodes can go with any choice and have many branches. Key points from the provided dataset form the basis of the judgements or tests.
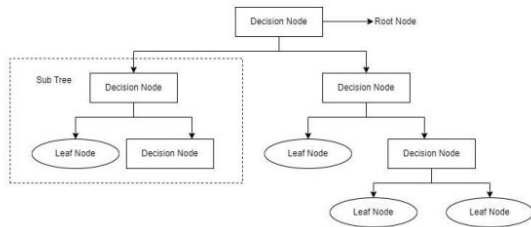


**Figure 1: Decision Tree**

It is a visual representation of all the possible solutions to a problem or choices given some parameters. The decision tree gets its name from the fact that, similar to a tree, it starts with a root hub and then grows branches to form a tree-like structure. We make use of the Truck algorithm—which stands for Order and Relapse Tree algorithm—to construct a tree. A simple question is all it takes for a decision tree to divide itself into subtrees based on the answer (Yes or No). The decision tree's overall structure is illustrated in the following graph.

### 3.2 Random Forest Classifier

One popular artificial intelligence calculation that fits nicely with the directed learning approach is Random Forest. Both Arrangement and Relapse problems in ML often make use of it. It is based on the principle of group realisation, which entails bringing together several classifiers to solve a complex problem and improve the model's display. As the title suggests, "Random Forest is a classifier that contains various decision trees on different subsets of the given dataset and takes the normal to work on the prescient precision of that dataset." The random forest does not rely on a single decision tree but rather averages out the predictions from all of them and uses the majority vote to arrive at a final prediction.

With a larger forest, we can avoid the problem of overfitting and achieve better accuracy.A Random Forest classifier uses a normal distribution to apply the predictive power of a dataset that has several decision trees trained on separate parts of the same dataset.

An increase in the forest's tree cover reduces the likelihood of overfitting and increases accuracy.

The first step in using a Random Forest is to create the forest itself by merging N decision trees. The second step is to assign expectations to each tree that was generated in the first stage.

The Functioning system can be made sense of in the below steps and outline:

**Step-1:** Randomly choose K pieces of relevant data from the prep set.

**Step-2:** Make use of the selected data points (subsets) to construct decision trees.

**Step-3:** In order to build decision trees, you must choose a value for N.

**Step-4:** Start again with Step 1.

**Step-5:** When new data becomes available, determine what each decision tree anticipates, and then distribute the updated data to the group that receives the most votes.

**Model:** Assume there is a dataset that contains different natural product pictures. Thus, this dataset is given to the Random forest classifier. The dataset is separated into subsets and given to every decision tree. During the preparation stage, every decision tree creates an expectation result, and when another information point happens, then in light of most of results, the Random Forest classifier predicts a ultimate choice.

### 3.3 Naïve Bayes algorithm

A controlled learning method known as the Naïve Bayes algorithm relies on the Bayes hypothesis and is employed to resolve order-related problems. It uses a high-dimensional preparation dataset mostly for text orders. The Naïve Bayes Classifier is an excellent and fundamental technique for creating fast AI models with the ability to generate fast predictions.

It makes predictions depending on how likely an item is to be true, as it is a probabilistic classifier. Spam filtration, Wistful analysis, and article classification are some well-known uses of the Naïve Bayes Algorithm.

The Bayes' theorem, often known as Bayes' standard or Bayes' regulation, is a tool for determining the probability of a hypothesis using historical data. The conditional probability is crucial. Here is the formula for Bayes' theorem:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Where,

The back probability is P(A|B): Observed event B's likelihood of hypothesis An.

Probability likelihood, denoted as P(B|A), is the chance that the evidence provided supports the

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validity of a hypothesis.

P(A) occurs before The probability of Probability of making an assumption before seeing the evidence

The minimal likelihood, denoted as P(B), is the likelihood of proof.

# 4. RESULTS

### 4.1 Functional Requirements

A One feature of a framework or component is its functional requirement. A capacity is shown as a collection of data sources, a behaviour, and outputs. Some examples of functional needs are estimates, technical details, information control and handling, and other features that define the goals of a framework. Prerequisites must be carried out to illustrate all instances in which the framework makes use of the functional demands. Supporting functional requirements are non-functional requirements, sometimes known as quality necessities, which impose plan or execution imperatives, such as security, unwavering quality, or execution necessities.

Functional requirements define the particular framework outputs, as described in requirements design. When compared to non-functional requirements, which dictate qualities like price and consistency of quality, this should seem different. The application engineering and spe cialised engineering of a framework are driven by functional requirements, whereas the former is driven by non-functional demands.

The focus of Functional Prerequisites is on the specific capabilities that the system conveys. Therefore, functional requirements are descriptions of the services that the system must provide.

- It is expected that the functional requirements of the framework will be completed and known in advance.

- To ensure satisfaction, it is necessary to detail all of the services that the client has requested.

- For criteria to be consistent, there must not be any ambiguity or grey areas in their description.

- As a rule, the requirements are shown in an original way. But functional framework requirements show the framework's potential in details, including its parts of feedback and outcomes, exceptional instances, etc.

- Gather the client's ID and secret phrase, and then match it with the relevant areas of the records. If a match is discovered, then go ahead and proceed; otherwise, raise an error message.

### 4.2 Non Functional Requirements

Non-functional The constraints of the framework are hinted at in the prerequisites. Exceptional aspects of the framework, such as consistency, response speed, and storage occupancy, or the selection of language, stage, execution tactics, and instruments, could be affected.

Client needs, budget constraints, association tactics, and other factors might inform the non-functional requirements.

**Execution prerequisite:** To provide a flawless display, every data entered will be reviewed by mark and no errors will be shown.

**Stage limitations:** Making a smart framework to foretell the adult level is the main goal.

**Exactness and Accuracy:** The information must be precise and accurate in order to proceed.

**Modifiability:** Details on the tasks needed to modify the product are prerequisites. Faculty effort (monthly) is often used as the estimate.

**Convenience:** The portability and ease of use of a cell phone make it an ideal tool for any situation.

**Unwavering quality:** Important information on the frequency of product failures. Disappointment ought to be defined clearly. Accessibility is a different kind of need than constant quality, so be careful not to confuse the two. Clearly state the outcomes of unsuccessful programming, how to avoid such outcomes, and a mechanism for error correction. Anticipation and a method for revision.

**Security:** security for your system and its data is an absolute must..

**Ease of use:** Factors influencing the difficulty of learning and working.

**The system:** Learning time is often when the necessities are provided.

The following table displays the application's system requirements.

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**Table 1. Resource Requirements Table**

| S.N | Hardware | Software | Libraries |
|---|---|---|---|
| 1 | Computer/Laptop | Windows 10/11, MacOS, Linux. | Numpy |
| 2 | RAM: 4GB or Above | Python 3.7 or above | SKlearn |
| 3 | Hard Disk | Visual Studio Code | Pandas |
| 4 | -- | -- | Tkinter |

## 5. CONCLUSION

Last but not least, FDPMLT, or the Framework for Disease Prediction using Machine Learning Techniques, is a huge leap forward in healthcare technology. By combining machine learning algorithms with predictive analytics, FDPMLT shows great promise in predicting and diagnosing possible illnesses in people. The resilience and reliability of the framework are enhanced by the thorough examination of varied datasets and the utilisation of advanced models. But we mustn't forget that the architecture needs constant tweaking and updating to meet new healthcare concerns and different data panoramas. When it comes to early diagnosis and preventative healthcare measures, FDPMLT is a great tool. It helps with prompt intervention and improves patient outcomes overall. With healthcare always changing, FDPMLT is well-positioned to lead the way for data-driven, personalised healthcare solutions. If FDPMLT is a success, it may change the way diseases are predicted, creating a proactive healthcare system that focuses on prevention rather than treatment and improving people's and communities' health in the long run.

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