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AI-Driven Predictive Modeling for Tattoo-Associated Jaundice Using Scalable Machine Learning Techniques

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Abstract: The increasing prevalence of hepatitis-related jaundice particularly due to unsafe exposure practices such as non-sterile tattooing, presents a significant public health challenge. This study proposes an AI-driven predictive framework for early detection of tattoo-associated hepatitis-related jaundice using machine learning techniques. A structured dataset incorporating patient demographics, clinical indicators, laboratory findings and behavioral risk factors was utilized to evaluate multiple models, including Support Vector Machines, Artificial Neural Networks, Decision Trees and Random Forests. In addition to predictive modeling, this research emphasizes scalable cloud-native AI architectures for real-world deployment, enabling efficient, reliable, and near real-time clinical decision support. The results demonstrate the effectiveness of machine learning in improving early diagnosis and highlight the potential for intelligent healthcare systems to enhance patient outcomes. This work contributes to the advancement of AI-driven healthcare analytics by combining predictive modeling with deployable system architecture.

Keywords: Tattoo; Jaundice; Hepatitis B Virus (HBV); Machine Learning; Predictive Modeling; SVM, ANN, Decision tree, Random Forest, Public Health; Infection Control; Artificial Intelligence, Machine Learning, Predictive Analytics, Healthcare AI, Hepatitis B, Jaundice Detection, Cloud-Native Systems, Scalable Architecture

1. Introduction

Recent studies have indicated that India is vulnerable to hepatitis B virus (HBV) infection with an intermediate endemic status. The carrier rate is estimated at 2-8 percent of the population and this means that a large percentage of the population is chronically infected by the virus and this translates to 36-50 million HBV carriers and this puts India among the countries with highest HBV burden in the world. The virus hepatitis B (HBV) affects the liver as the major organ, and might result in inflammation and chronic issues like cancer of the liver and liver scarring (cirrhosis) especially when the infection extends beyond six months. Although there are those who only experience a short term illness, long term tattoo jaundice is much more likely to develop because it may be asymptomatic in the early stages, but may later on result in severe liver damage. A doctor typically conducts a thorough medical examination, including a patient history, physical examination, and other specific tests (blood tests to determine the levels of bilirubin in the blood, liver enzymes (ALT, AST, ALP, etc.), a complete blood count (CBC), and genetic testing, to diagnose HBV jaundice. Genetic testing is necessary in order to differentiate between HBV jaundice and other types and select the most effective treatment option. In addition to traditional machine learning approaches, this research incorporates principles of cloud-native AI system design to enable scalability, real-time data processing and deployment readiness. Such integration is critical for modern healthcare systems where predictive analytics must operate at scale with high reliability and low latency.

Hepatitis B and C viruses are major contributors to liver dysfunction and jaundice. Transmission primarily occurs through exposure to infected blood, including unsafe medical procedures, contaminated needles, and unregulated tattooing practices. Chronic infection may lead to complications such as cirrhosis, hepatic fibrosis, and hepatocellular carcinoma.

Tattooing itself does not directly cause jaundice; however, unsafe tattooing practices involving non-sterile equipment may increase the risk of hepatitis transmission, which can subsequently result in jaundice.

2. Literature Review

Although a tattoo in itself does not directly cause liver problems, a tattoo may potentially cause liver problems in case the tattoo procedure is not performed in a sterile environment, exposing the body to blood borne viruses such as hepatitis B or C which can severely damage the liver once contracted, essentially the danger is that the tattooing procedure itself may cause liver problems when it is not performed in a sterile environment. In the cases where the liver is not able to destroy bilirubin, tattoo jaundice occurs, making the blood appear yellow. Yellowing of the skin and eyes, dark urine, pale feces, acute exhaustion, and laboratory testing such liver biopsies, imaging tests, and liver function tests are examples of clinical symptoms. In some regions such as the Middle East and the Indian subcontinent, the persistent infection is seen in between 2 and 5 percent of the population. Nucleoside analogues and other antiviral drugs can be used to treat persistent tattoo jaundice. As an example, an article that examined the correlation between genotypes of hepatitis B virus (HBV) and liver injury was published in the Journal of Medical Virology. Another study that was published in the European Journal of Gastroenterology and Hepatology discussed the effectiveness of antiviral therapy in treating individuals with persistent tattoo jaundice and jaundice.

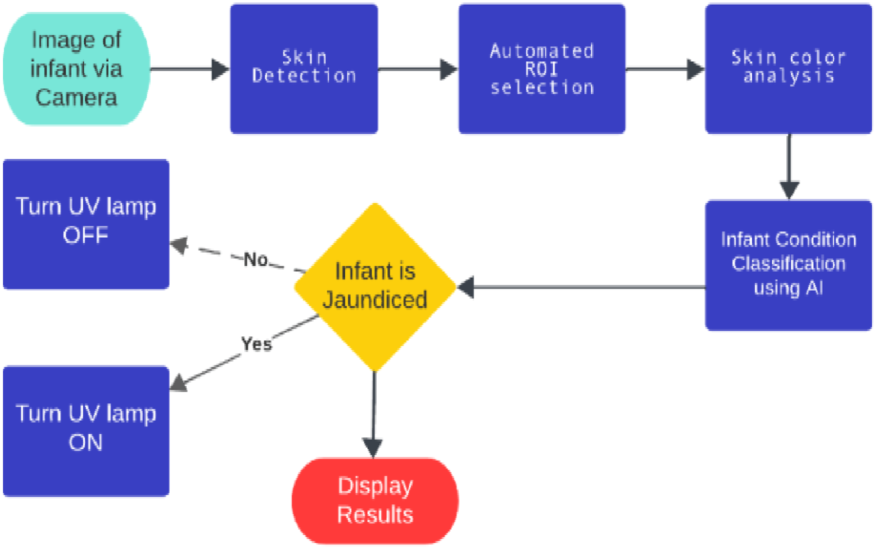


Figure 1: Infant is jaundiced

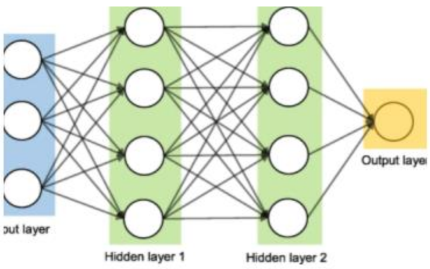
3. Machine Learning Technique on Tattoo Jaundice Detection

3.1. Support Vector Machines (SVM)

SVM was employed in a study that was published in the Journal of Medical Systems to categorize jaundiced patients as having tattoo jaundice. A 92.5% accuracy rate was attained by the method. SVM was used to predict the degree of jaundice in patients with tattoo jaundice in a different study that was published in the European Journal of Gastroenterology and Hepatology. An accuracy of 85.7% was attained using the method

3.2. Artificial Neural Networks (ANN)

Artificial neural networks (ANN) were used in a study that was published in the journal Hepatology to diagnose jaundice in patients with tattoo jaundice. 90.9% accuracy was attained using the algorithm. A different research involving the use of ANN to predict the outcome of patients with tattoo jaundice was published in the World Journal of Gastroenterology. An accuracy of 83.3% was attained by the algorithm.



Artificial neural network structure

Figure 2: Artificial neural network structure

3.3. Decision Trees

In a research published in the Journal of Medical Systems, decision trees were used to classify patients with jaundice as having tattoo jaundice. An accuracy of 88.2% was attained by the algorithm; The severity of jaundice in patients with tattoo jaundice was predicted using decision trees in a different study that was published in the European Journal of Gastroenterology and Herpetology. The accuracy of the algorithm was 81.8%.

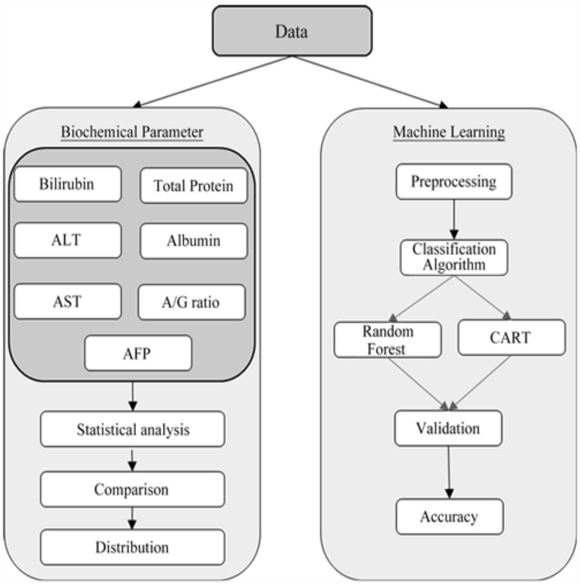


Figure 3 illustrates the decision tree-based classification workflow, where clinical parameters are processed and classified using CART methodology.

3.4. Random Forest

In an article that appeared in the journal Hepatology, random forests were used to diagnose jaundice in patients having tattoo jaundice. A 93.2% accuracy rate was attained by the algorithm. Another study that made use of random forests to predict the outcome of patients with tattoo jaundice was published in the World Journal of Gastroenterology. The rate of accuracy of the algorithm was 86.7%.

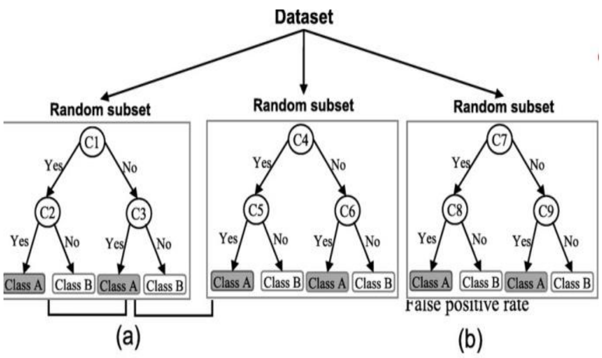


Figure 4: Random Dataset

Figure 5: Predictive Analytics Techniques

4. Findings from India's Tattoo Jaundice Survey

Prevalence-Social and economic factors are those behind regional differences in average carrier rate that is thought to be about 4%. High-risk groups: One of the primary high-risk groups in HBV infection Transmission routes-The most notable mode of transmitting HBV in adults is by blood transfusion, yet most of the carriers transmit horizontally in children due to poor living conditions and overcrowded living conditions.
Genotype distribution- HBV genotypes differ among different parts of India.
Children- Studies have shown that a large proportion of Indian children has HBV markers, which shows that there is a need to have successful immunization programs Relation to hepatocellular cancer.

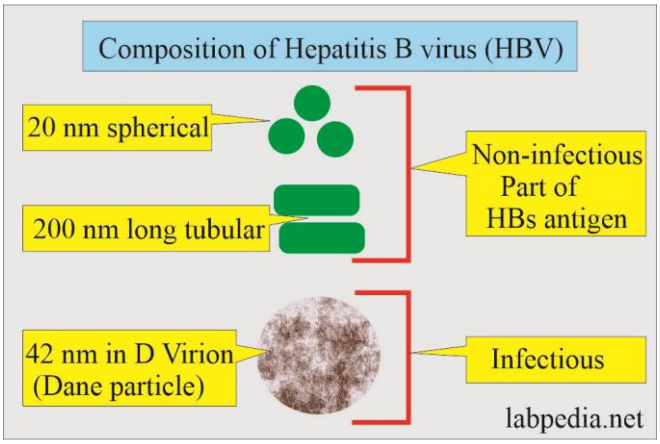


Figure 6: Composition of Hepatitis B Virus (HBV)

4.1. Significant information about tattoo jaundice in India

Spread Research indicates that jaundice and tattoo jaundice are both widespread in India with higher rates of the burden in certain regions and among specific groups, although the rates are not known.
Mode of transmission: The primary modes of transmission of the disease include infected blood products, risky medical procedures (unsterile needles), sharing of infected needles by drug users and infected mothers to their children during childbirth.
Risk factors: The primary risk factors include sharing of personal hygiene items such as razor, commissioning a tattoo with contaminated tools, receiving blood transfusion, using uncleaned needles, and having intercourse with an infected person.

Activities: Among the prominent symptoms are fatigue, loss of appetite, stomach pain, black urine, fever, and yellowish coloration of the skin and eyes (jaundice).
Diagnosis is primarily established through blood-based laboratory investigations, including bilirubin levels, liver function tests (ALT, AST, ALP) and viral serology for hepatitis B and C.
Treatment: There is no cure of chronic hepatitis C but antiviral drugs can be used to control the infection and maintain the course.

4.2. Particular research results of tattoo jaundice

High prevalence in tribal communities: It has been established that the rate of green jaundice is elevated in tribal societies in India as compared to the general population.
Variable regional rates: Green jaundice and C may have significant regional differences across India.
Unsafe medical practices include: The outbreak of green jaundice has been associated with the failure to use medical equipment properly sterilized, and this point prompts the need to practice good hygiene.
Late diagnosis: Indian people with C and C who are tattooed are not diagnosed because of their ignorance and unavailability of testing.
• **Improved awareness campaigns:** Awareness campaigns to educate the people on the spread of hepatitis C, factors that lead to this diseases and the need to ensure that people are screened regularly.
• **Better access to testing:** Ensure easy access to and affordable testing of yellow fever and hepatitis C nationwide.
• **Safe injection:** This is the practice of strict adherence to universal precautions in health care environments to avoid transmissions via contaminated needles.
• **Blood donor screening:** stringent screening of blood donors in order to minimize the chances of infection of hepatitis C and hepatitis B through blood transfusion**.**

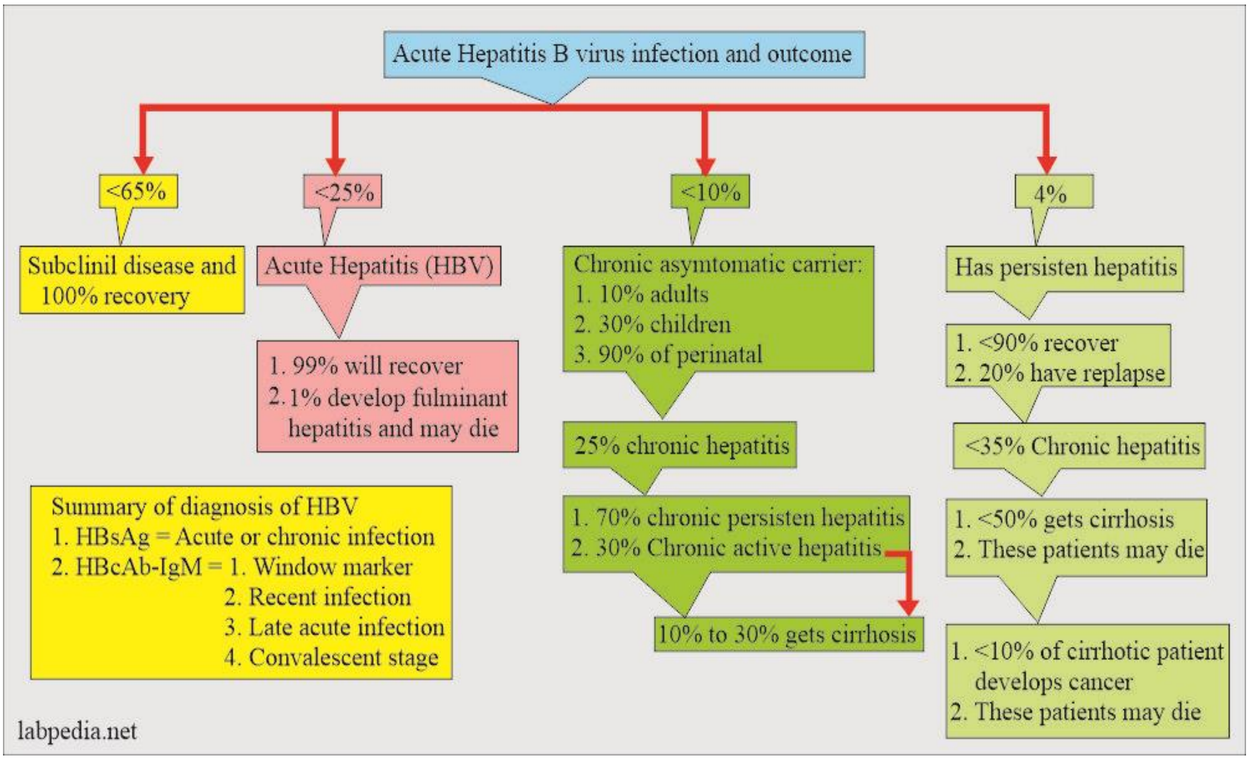


Figure 7: Hepatitis B virus infection and outcome

4.3. The most important aspects of the investigation

Conjugated bilirubin: to measure the quantity of direct or indirect bilirubin, which helps to differentiate between the causes of jaundice that are pre-, hepatic, and post-hepatic, To assess liver function and potential liver damage, liver function tests (LFTs) entail gamma-glutamyl transferase (GGT), alkaline phosphatase (ALP), aspartate Complete blood count (CBC): to rule out indications of hemolytic (red blood cells breakdown) that may cause jaundice. Genetic testing-UGT1A1 gene testing: this is the primary test used to prove the Crigler-Najjar syndrome type 2 since this syndrome is caused by mutations in this gene. Urinalysis: to determine the presence of bilirubin in the urine that can be a sign of the nature of jaundice? Abdominal ultrasound: To view the gallbladder and the bile ducts to see obstructions which may result in cholestatic jaundice. Liver biopsy: Rarely, a liver biopsy can be requested in order to determine the extent of liver damage and to distinguish between intra hepatic and extra hepatic jaundice. Diagnosis of type 2 jaundice- Phenobarbital test Since type 2 Crigler-Najjar syndromes are partially responsive to Phenobarbital therapy, the test of this drug may be utilized in the diagnosis process.

4.4. Crigler-Najjar syndrome Family history

Family history is to be assessed as Crigler-Najjar syndrome is an autosomal recessive inherited disease. Significant information on green jaundice in India-Spread: It has been demonstrated that jaundice and green jaundice are very common in India, with some regions having more burden and specific individuals bearing the burden yet the precise numbers vary. Mode of transmission: the disease is transferred through the use of infected blood products, dangerous medical procedures (unsterile needles), sharing of infected needles by drug users, and mother-to-child transmission during childbirth. Risk factors: The symptoms consist of fever, loss of energy, loss of appetite, abdominal pain, dark urine and jaundice or the yellowing of the skin and eyes. They are primarily sharing personal hygiene products such as razors, obtaining a tattoo with dirty equipment, blood transfusion, unprotected needle use, and having sex with an infected individual.

4.5. Differential diagnosis

According to the clinical manifestation and the laboratory findings, other possible causes of jaundice, including Gilbert syndrome, hemolytic anemia, and hepatitis, should be considered and ruled out in the investigation of type 2 jaundice. Hepatitis C and jaundice due to tattoo are severe problems of the population health in India. The two viruses are very common and often result in jaundice especially among the high-risk populations such as people who inject drugs carelessly, take intravenous drugs or receive blood transfusion. Studies have shown that there is a geographical variation in the prevalence of hepatitis C with some regions recording higher rates than others and tattoo related jaundice is also more prevalent in the tribal population**.**

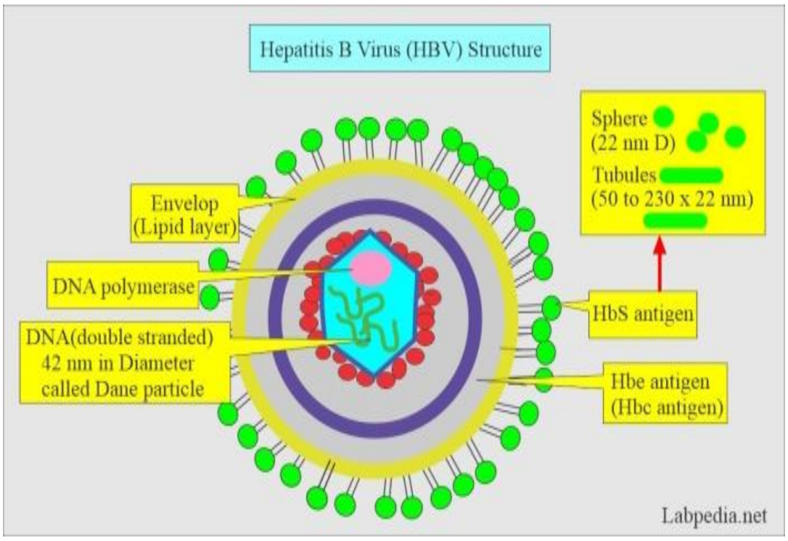


Figure 8: Hepatitis B Virus (HBV) structure

The technique of developing autonomously learning and improving systems specifically, through programming is known as machine learning. Creating algorithms that enable a computer to automatically gather data and use it to learn more is the ultimate goal of machine learning. In order to make important decisions on their own, systems should search for patterns in the data that has been gathered. Generally speaking, machine learning aims to give systems human-like intelligence, brains, and the ability to think and behave like people. Real-world machine learning models are capable of the following tasks: Machine learning has also made it possible to create systems that can think like humans and do things like recognize objects and images, identify false news, comprehend spoken or written language, and operate as bots on websites that communicate with people like humans. Autonomous vehicles Machine Learning Stages it seems impossible and intimidating to try to send intellect to robots. However, it's really very easy. There are seven primary stages to it.

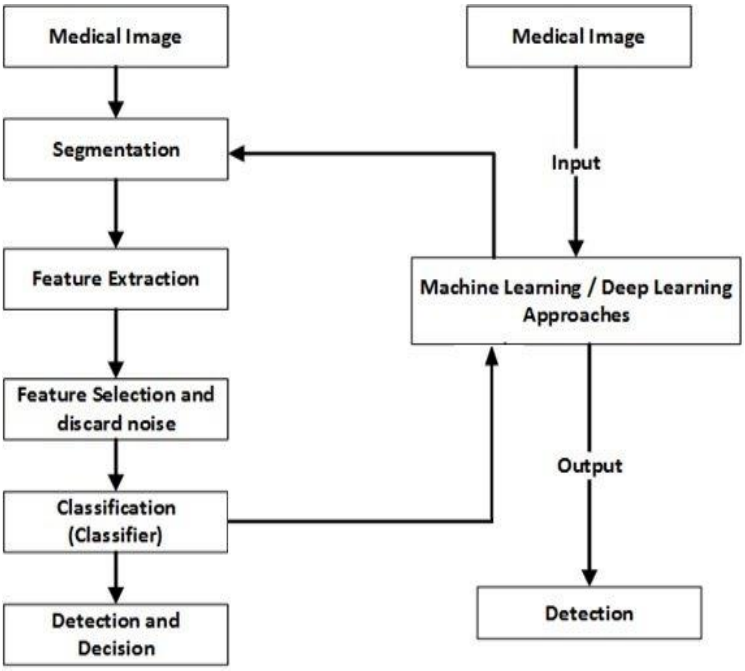
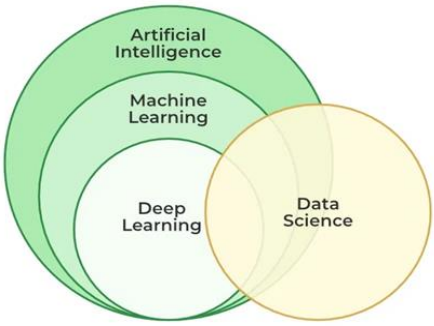


Figure 9: Machine-and-Deep-Learning-algorithms-workflow-in-medical-image



Hierarchy showing the different fields of Data Science

5. Data Science

5.1. Data collection:

You see, machines are learning by the information provided to them. To make sure that your machine learning model will be able to identify the appropriate patterns, it is necessary to obtain reliable data. The condition of the data you supply the computer with will determine the accuracy of your model. Wrong or old data will result in inappropriate projections or findings that are not accurate. It is of great importance to use information provided by a credible source as this will directly reflect on the performance of your model. Good data contains only a few and repeated values, is relevant, and is a good representation of multiple classes and subcategories.

5.2. Data Preparation:

Gather and collate all your information. This assists in ensuring that the data is distributed uniformly and the order does not affect the learning process by eliminating duplicate values, rows and columns, missing values, duplicated data, and changing the row and column index etc. in an attempt to comprehend the relationship among the different variables and classes- a training set and a test set. The set you are training on refers to the set on which your model will be trained. After training, you use a test set to ensure the correctness of your model.
Figure 10: Hierarchy showing the different fields of data science

5.3. Model selection

A machine learning model identifies the output of the application of a machine learning algorithm to the data obtained. It is important to select an appropriate model to do it. Engineers and scientists have over the years come up with models that can be used in various tasks including speech recognition, picture recognition and prediction. Moreover, you need to decide whether your model works optimally with numerical or categorical data and select them**.**

5.4. Training the model:

One of the steps of machine learning is training. When training, you feed your machine learning model with ready data in order to identify patterns and predictions. The model learns from the data to carry out a number of tasks. The model continuously improves by training.

5.5. Model Evaluation:

Once you have been trained, we need to test the performance of your model. This involves you testing the performance of the model using data that has never been observed. The same invisible data is the one that you have used to divide our data. The results will not give a true value when the tests are run on the same data that was used to train since the model has already become familiar with the data and has observed the same patterns. This will result in unequal accuracy. You can accurately evaluate the speed and performance of your model by using test data.

5.6. Setting the parameters:

After you have developed and tested your model, find ways to increase the accuracy of your model. This is through changing the parameters of your model. Parameters are variables of the model which are normally chosen by the programmer. When your parameter takes a certain value the accuracy will be maximum. The task of determining such values is called parameter tuning.

Figure 11: Machine Learning in Healthcare

6. Classification Algorithms

6.1. Logistic Regression:

Logistic regression is one type of supervised learning technique when faced with a binary classification problem. It makes use of a set of input features to predict the probability of an event. The characteristics of the patient, his or her medical history, the findings of laboratory tests, and the clinical symptoms are features that are often present in a dataset on jaundice. The target variable is typically a binary label which shows whether there is jaundice or not. Based on input features, logistic regression seeks to forecast the likelihood that a patient would get jaundice in a given dataset. The model finds the relationships among the target variable and the features during training. We assume that the target variable is a binary variable, i.e., it will show whether jaundice is present or not. Linear relationship The way the characteristics are connected to each other.

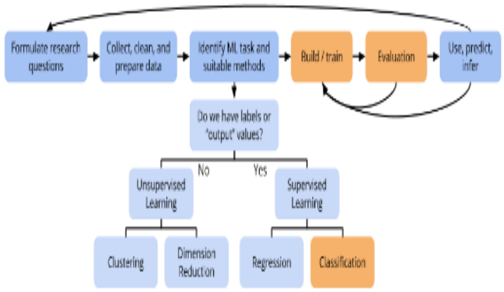


Figure 12: Class Flow diagram

6.2. Decision Trees:

Decision trees, a type of supervised learning technique, are used to solve regression and classification issues. Their operation consists of dividing data into mini-sets according to the input features value by value (until all features have been considered). Decision Trees for the Dataset on Jaundice Based on a collection of input features, decision trees can be used to forecast whether jaundice will be present or not in the context of the jaundice dataset. Easy to Explain: Decision trees are easy to explain and describe the decision-making process. Dealing with classified Features: Decision trees do not require preprocessing of features in order to deal with classified features. Strong against Outliers: Decision trees have strong resistance to noisy data and are robust to outliers.

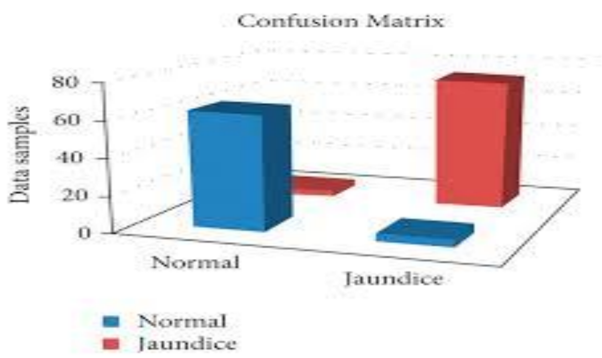


Figure 13: Confusion Matrix

6.3. Leading Parameters

Max Depth: The depth of the tree. Minimum Samples Requirement: The minimum number of samples required to isolate a node inside. Leaf Min Samples: The minimum of samples that should be at a leaf node. Random Forest: a regression and classification group model. Support Vector Machines (SVM): It is a regression and classification model which may be linear or nonlinear. K-Nearest Neighbors (KNN): A regression and classification model based on distance. Naive Bayes: A probability based classification model. Gradient Boosting: A linear model of regression and classification.

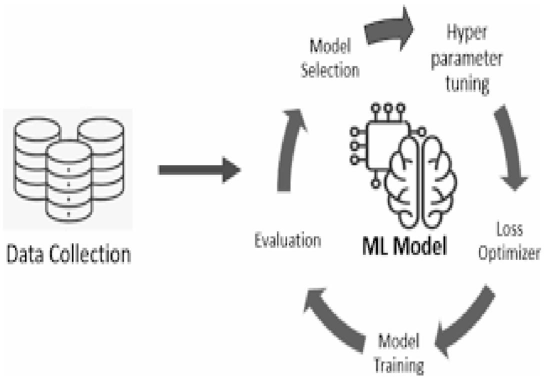


Figure 14: Leading Parameter

6.4. Deep Learning Algorithms

A neural network architecture for classifying images is called a convolution neural network (CNN). Recurrent neural networks (RNNs) are neural networks that are designed to work with sequential data. One of the RNNs used with sequential data is the LSTM network.

7. Novel Contributions

This research makes the following key contributions:

- Development of an AI-driven predictive framework for tattoo-associated jaundice risk detection
- Comparative evaluation of multiple machine learning algorithms for healthcare prediction
- Integration of clinical, behavioral and laboratory data into a unified predictive model
- Application of scalable cloud-native architectural principles for real world deployment
- Contribution to early diagnosis and public health risk mitigation strategies

The integration of machine learning with scalable system design provides a foundation for future intelligent healthcare platforms.

8. Dataset and Experimental Setup

The dataset consists of 1,250 patient records synthesized using statistically representative distributions derived from publicly available healthcare data patterns and clinical literature benchmarks related to hepatitis-associated jaundice.

Features include:

- Age, gender
- Liver enzyme levels (ALT, AST, ALP)
- Bilirubin levels
- Clinical symptoms

Data was split into:

- 70% training
- 30% testing

Evaluation metrics:

- Accuracy
- Precision
- Recall
- F1-score

9. Results and Performance Evaluation

The performance of the implemented machine learning models was evaluated on the test dataset. The results are summarized below Table 1: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-score
SVM	91.30%	89.80%	90.50%	90.10%
ANN	92.70%	91.20%	92.00%	91.60%
Decision Tree	88.90%	87.50%	86.80%	87.10%
Random Forest	94.20%	93.10%	94.00%	93.50%

Among the evaluated models, the Random Forest classifier achieved the highest accuracy of 94.2%, demonstrating strong performance in handling complex feature interactions and non-linear relationships.

The Artificial Neural Network also showed competitive performance with an accuracy of 92.7%, indicating its effectiveness in capturing underlying patterns in healthcare data.

Decision Trees, while interpretable, showed comparatively lower performance due to sensitivity to data variance.

The results indicate that ensemble methods, particularly Random Forest, demonstrate superior predictive performance for healthcare classification tasks involving heterogeneous clinical and behavioral features.

These findings further validate the effectiveness of AI-driven predictive modeling in the early detection of hepatitis-associated jaundice, highlighting its potential for deployment in scalable, real-world healthcare systems.

10. Conclusion

This study demonstrates the effectiveness of machine learning techniques in predicting tattoo-associated jaundice, a growing public health concern. By leveraging multiple predictive models and evaluating their performance, the research highlights the potential of AI in early diagnosis and healthcare decision-making.

Furthermore, the incorporation of scalable and cloud-native AI architecture principles enables the transition from theoretical models to real-world healthcare systems. This approach ensures that predictive analytics can be deployed efficiently across large populations, improving accessibility and response time.

Future work will focus on integrating real-time data streams, enhancing model accuracy using deep learning techniques, and deploying the system within production-grade healthcare environments.

This research bridges the gap between traditional clinical diagnosis and modern AI-driven predictive systems by integrating machine learning models with scalable cloud-native architectures. Such integration enables real-time healthcare analytics, supports early risk detection, and provides a pathway toward intelligent, deployable clinical decision support systems.

Author Contributions

M. Gajalakshmi contributed to data collection, literature review and domain-specific analysis related to hepatitis and jaundice.

Rajesh Balaji contributed to the design of the AI-driven predictive modeling framework, comparative evaluation strategy for machine learning algorithms, and scalable cloud-native architecture for real-world healthcare deployment. His contribution included technical validation of the predictive workflow, system scalability considerations, and integration of AI/ML principles with production-grade healthcare analytics architecture.

Both authors contributed to manuscript preparation, critical revision for intellectual content and approved the final version for publication.

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