

# A Decision Support System for Health Management: Integrating Big Data and Machine Learning in Information Systems

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## ARTICLE INFO

## ABSTRACT

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Healthcare tools are changing quickly, and the amount of medical data is growing. This has made health management more difficult. Decision Support Systems (DSS) are important tools that can help with these problems by giving doctors smart advice to help them make smart choices. Combining Big Data analytics and Machine Learning (ML) methods in a Decision Support System is what this study suggests as a way to handle health better. By using big data sets like electronic health records (EHRs), patient tracking systems, genetic data, and other health-related data, the goal is to improve the quality and efficiency of healthcare services. The suggested DSS structure is based on three main parts: combining data, handling it analytically, and making choices. First, data integration is all about bringing together different sources of data, making sure the data is correct, and building a single platform that makes it easy to find the information you need. Big Data tools, like Hadoop and Spark, are used to deal with huge amounts of organized and random data at the same time. Machine learning models, especially controlled and unstructured learning algorithms, are used to get useful information from these datasets. For example, they can find trends, guess how diseases will progress, and suggest individual treatment plans. Second, the system's analytical processing layer uses advanced machine learning methods like classification, regression, and grouping to help with decision-making and predictive analytics. These models are trained on a lot of healthcare data, which gives doctors useful information about how diseases grow, what causes them, and the best ways to treat them. The system is always learning, which means that models can be improved based on new data. This makes the system more accurate and flexible.

**Keywords:** Decision Support System (DSS), Big Data, Machine Learning, Healthcare Analytics, Predictive Modeling.

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## I. INTRODUCTION

In the past few years, technology has quickly improved in the healthcare field. This has caused the amount and complexity of medical data to grow at an exponential rate. These changes have been good, but they have also caused a lot of problems for healthcare workers, like making it harder to organize, process, and analyze data. As a result, using this data to make smart decisions has become an important part of modern health management. A Decision

Support System (DSS) is an important tool in this situation because it gives healthcare professionals smart suggestions based on data analysis. This can greatly improve the process of making choices about patient care, evaluation, and treatment plans. A decision support system (DSS) is a computer program that looks at a lot of data, gives insights, and makes suggestions to help people make decisions [1]. These systems have been used for a long time in many different fields, but their use in healthcare has gotten a lot of attention lately because managing health care is getting more complicated. Adding cutting edge technologies like Big Data analytics and Machine Learning (ML) to DSS can make the decision-making process a lot better as the healthcare industry becomes more data-driven. Big Data is the term for very large and complicated sets of data that are hard for regular data processing methods to handle. A type of artificial intelligence (AI) called machine learning lets computers learn from data, find patterns, and make choices or guesses without being explicitly programmed to do so. Putting these two advances together in a DSS structure makes for a strong wellbeing administration option. The way that medical data is assembled, kept, and inspected has changed since Huge Information was presented to healthcare.

A lot of data is made by electronic health records (EHRs), smart tech, patient following systems, hereditary information, and other sources. This data can be utilized to memorize more about patients' health, illness patterns, and treatment results. Conventional frameworks, on the other hand, have inconvenience handling and analyzing this data because of the huge amount and variety of these information sources. Healthcare companies can handle enormous datasets more quickly, discover secret patterns, and get insights that were difficult to discover some time recently they begun utilizing Enormous Information devices. This makes a difference specialists make more accurate diagnoses, figure out the leading ways to treat individuals, and lower their dangers. Machine Learning, on the other hand, makes it less demanding to figure what will happen and tailor treatment to each individual [2]. By utilizing machine learning calculations on both past and current wellbeing information, specialists can make forecasts approximately how infections will advance, how patients will do, and what issues might emerge. For case, ML models can be utilized to figure out how likely it is that a quiet will get a certain sickness. This lets specialists begin treating them earlier and make personalized care plans for them.

ML can moreover offer assistance specialists make choices by finding the finest medicines for each quiet based on their special characteristics. This makes medicines more effective and progresses patient results. Huge Information and Machine Learning, on the other hand, have a parcel of guarantee for making strides wellbeing administration. Be that as it may, putting these advances together in a way that works well with others isn't simple. One of the most issues is that coordination information is difficult to do. A part of the time, healthcare information is broken up and comes from distinctive places with diverse forms, sorts, and benchmarks. For any DSS to work, these diverse information sources must be brought together into a single framework that can handle and look at the data well [3]. Moreover, the quality of the data is exceptionally vital. Information that's off-base or missing can cause figures and choices to be off-base, which harms the DSS's value. So, making beyond any doubt you have got high-quality, exact information is exceptionally critical. Additionally, Machine Learning systems can make guesses and suggestions more accurate, but they need to keep learning and changing. This means that a DSS must be able to keep its models up to date as new data comes in. This keeps the system useful and correct over time. Using real-time decision help is another important thing to think about. Healthcare professionals need quick, practical information that they can use right away in the office to make smart choices [4].

## II. RELATED WORK

In the past few years, a lot of study and development has gone into combining Big Data and Machine Learning (ML) in hospital Decision Support Systems (DSS). A lot of research has been done on how these technologies can improve health management by making it easier to diagnose problems, plan treatments, and decide how to use resources. This part gives an outline of a few critical related work that has made a difference make shrewdly healthcare frameworks conceivable. A enormous portion of healthcare DSS think about is looking into how to utilize Big Information analytics. A number of thinks about have appeared that enormous healthcare records, like Electronic Health Records (EHRs), genetic information, and understanding following frameworks, can be utilized to discover valuable data that can offer assistance individuals make way better choices [5]. Raghupathi and Raghupathi for example, looked into how Enormous Information analytics may be utilized to figure how infections would advance and make therapeutic care better. By looking at a lot of old patient data, their work showed how prescient analytics might be utilized to assist oversee long-term illnesses like diabetes and heart issues. Utilizing Huge Information devices like Hadoop and Spark, healthcare workers can handle and look at information in

genuine time, which lets them act rapidly. The utilize of machine learning to assist specialists make choices is another critical region of study.

ML techniques like administered learning (like choice trees and back vector machines) and unstructured learning (like clustering) have been utilized a parcel to foresee how patients will do, gather infections, and make personalized treatment plans. One vital illustration is the consider by Rajkomar et al. which utilized EHR information and profound learning models to figure how patients would do. Their comes about appeared that ML models may make analyze much more precise and offer assistance specialists make way better choices based on detailed data almost each persistent. A parcel of specialists have been looking into how machine learning frameworks can offer assistance make treatment recommendations that are custom-made to each patient's needs [6]. For case, Kourou et al. utilized ML strategies to create a demonstrate for foreseeing the result of cancer. To figure out how likely it was that the cancer would come back, they utilized data from a lot of different sources, such as the patient's socioeconomics, clinical characteristics, and hereditary qualities. This kind of personalized choice bolster is getting more consideration in cancer, where being able to tailor treatment plans to each patient's one of a kind characteristics might lead to better results. Even though these considers appear a lot of promise, it'll still be difficult to combine Enormous Information and ML into a single DSS. Issues with information quality, joining information, and framework interaction are still stopping a lot of individuals from utilizing it [7].

Table 1: Summary of Related work

Approach	Future Trend	Benefits	Impact
Healthcare decision support systems leveraging machine learning for patient diagnostics.	Integration of real-time data analytics using IoT in health management systems.	Improved decision-making through predictive analytics.	Better patient outcomes through personalized care.
Use of big data analytics for predictive healthcare models.	Growth of AI-driven predictive health monitoring systems.	Enhanced disease prediction and prevention.	Reduced healthcare costs by preventing chronic conditions.
Data integration in electronic health records for optimized decision support [8].	Cloud-based solutions for scalable health data management.	Increased access to patient data across multiple providers.	Improved continuity of care and reduced medical errors.
Machine learning models for predicting patient readmission risk.	Advancements in deep learning for real-time health data analysis.	Early intervention leading to better patient prognosis.	Lower hospital readmission rates and reduced healthcare strain.
Use of natural language processing (NLP) for medical records analysis.	Expanded use of NLP for extracting actionable insights from unstructured data.	Efficient handling of large volumes of unstructured health data.	Streamlined patient care through faster data processing.
Big data platforms for collaborative decision support in healthcare.	Integration of AI and blockchain for secure, transparent health data sharing.	Enhanced collaboration between healthcare providers.	Increased trust in healthcare systems due to data security and transparency.
Personalized medicine approaches through big data and ML integration. [9]	Rise of precision medicine tailored to individual genetic profiles.	Improved treatment outcomes due to personalized care plans.	Reduced adverse drug reactions and optimized drug efficacy.
Real-time health monitoring systems using big data analytics.	Continuous monitoring with wearable health devices providing actionable insights.	Continuous, non-invasive monitoring for chronic disease management.	Empowered patients in managing their health conditions.
AI-based recommendation systems for patient treatment plans.	Use of explainable AI to enhance transparency and trust in decision-making.	Faster and more accurate treatment decisions.	Increased patient satisfaction due to tailored treatments.

Decision support systems for managing hospital resources using predictive analytics [10].	Development of AI to optimize hospital resource allocation in real time.	Better resource utilization and reduced operational costs.	Increased hospital efficiency and reduced wait times for patients.
Integration of genomics data in health management systems for personalized care.	AI-driven genetic data analysis for disease risk prediction.	Enhanced diagnosis through genomic data.	Early detection of genetic predispositions leading to preventive care.
Integration of patient-generated health data in decision support systems.	Expansion of mobile health apps and wearables for real-time data collection.	Empowerment of patients through self-monitoring and reporting.	Improved health outcomes through active patient participation in care.
Research on optimizing machine learning algorithms for large-scale healthcare data.	Research into adaptive ML models for personalized health recommendations.	More accurate and individualized patient care.	Revolutionized healthcare with AI-driven, customized treatment plans.

### III. OVERVIEW OF DECISION SUPPORT SYSTEMS (DSS)

#### A. Definition and components of DSS

Decision Support Systems (DSS) are computerized information systems that are meant to help people make decisions by giving them the right data, models, and analysis tools to help them make smart choices. DSS are usually used in situations where making decisions is hard and human opinion and knowledge are very important. DSS are different from standard management information systems (MIS), which are mostly used for making regular decisions. DSS are made to help people make non-routine, strategic, or ad hoc decisions, often when there is doubt or a lot of information to consider [11]. A DSS is usually made up of four main parts. The first part is the Data Management Component, which is what every DSS is built on. It is made up of databases or data banks that store important data. This data can come from many places, such as internal sources like transactional systems or external sources like market data or sensor inputs. The data management part makes sure that the data is well-organized, kept quickly, and easy to get to so that people can get the information they need to make smart decisions. This is the second part, which is the Model Management Composite. This part has mathematical and analytical tools that are used to look at data and come up with different options for making decisions. These models can be as simple as math problems or as complicated as exercises and methods for finding the best solution. The DSS helps users weigh different choice options and guess what might happen in different situations by changing data using these models. This lets decision-makers pick the best course of action. One of the third parts of a DSS is the Knowledge Management Component. It uses subject knowledge, rules, and patterns to help make decisions [12]. These things are what give the system its "intelligence." This part helps people who make decisions understand the results of handling data by giving them information based on past experiences, best practices, or expert knowledge. This makes sure that the choices made are in line with the organization's goals and objectives.

#### B. Types of DSS in healthcare

Decision Support Systems (DSS) are utilized in healthcare to help specialists and directors make savvy choices around how to care for patients, make treatment plans, diagnose issues, and handle assets. Diverse sorts of DSS are made to meet particular needs within the healthcare field. They all use advanced calculations, prescient models, and data analysis to help individuals make decisions. These are the most kinds of DSS utilized in healthcare:

- **Clinical Decision Support Systems (CDSS):** One of the most common types of DSS used in healthcare is the clinical decision support system. They help patients do better by helping with evaluation, cutting down on drug mistakes, and offering personalized treatment choices. Based on a patient's medical background, a CDSS might tell a doctor about a possible medicine conflict or offer other treatments [13].
- **Operational DSS:** In healthcare, operational DSS are used to make day-to-day tasks more efficient and effective. These tools help hospitals handle their resources, such as their workers, schedules, and stock. By looking at old data and guessing how patients will move through the system, operational DSS help

healthcare managers make the best use of their resources, get more patients through, and lower their costs. For example, these systems can guess how many patients will be in a certain area or when the busiest times are in emergency rooms, which helps managers better plan their staffing.

- **Management DSS:** These tools help healthcare groups' managers make decisions. Their main jobs are to make plans for the future, handle money, and come up with policies. A lot of the time, management DSS involve looking at big sets of data, like financial reports, patient happiness surveys, and hospital performance numbers. This helps managers make smart choices about how to spend money, allocate resources, and plan for the future [14].
- **Personal Health DSS:** Personal Health Decision Support Systems are made to help people take care of their own health. People who use these systems get unique suggestions based on their medical background, the choices they make about their lifestyle, and real-time health information from gadgets they wear.

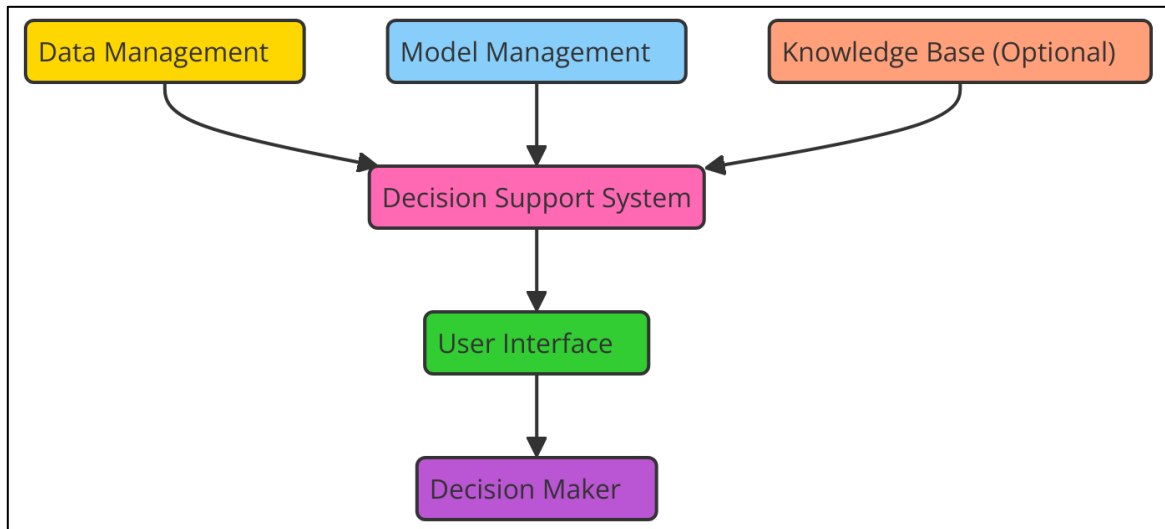


Figure 1: Overview of Decision Support Systems (DSS)

#### IV. BIG DATA IN HEALTH MANAGEMENT

##### A. Definition and characteristics of Big Data

Big Data refers to files that are so big and complicated that they can't be managed, stored, or analyzed easily with traditional data processing methods. As it relates to health management, "Big Data" includes a lot of different types of health data, such as genetic data, patient tracking systems, medical images, smart tech, social media health data, and more. When you combine these different types of data, you can learn more about patient health, disease trends, treatment results, and how healthcare is run. The amount of data is one of the most important things about "Big Data." A huge amount of health data is created every day from places like hospitals, clinics, medical gadgets, and smart tech that patients wear [17]. It can be structured (like numbers in medical records), semi-structured (like doctor's notes), or not structured at all (like medical pictures or movies). Because there is so much of it, it is hard to store and process. However, it is also possible to find useful insights that can improve healthcare results. Variety is another thing that makes Big Data unique. There are different kinds of healthcare data, such as organized data (like lab test results) and unstructured data (like talks between doctors and patients and medical pictures). To mix these different kinds of data in a way that makes sense, you need to use advanced data integration and processing methods. Speed is the rate at which healthcare data is created and needs to be handled [18]. For instance, real-time info from smart tech or patient tracking systems needs to be analyzed right away so that doctors can make quick decisions. For real-time reports, analysis, and actions in health management, it's important to be able to handle data quickly. Another feature of Big Data is veracity, which refers to the quality and doubt of the data. It's very important to check the quality and accuracy of healthcare data before using it for research because it's often missing, unreliable, or noisy.

## **B. Sources of Big Data in healthcare (e.g., electronic health records, sensors, wearables)**

Big Data in healthcare comes from many different places, and each one gives us new information that we can use to make decisions better, improve patient care, and simplify processes. Electronic health records (EHRs), devices, smart tech, medical images, and genetic data are some of these sources. EHRs, or electronic health records, are one of the most important sources of Big Data in healthcare. EHRs hold a lot of information about a patient, like their medical background, illnesses, medicines, lab results, vaccination records, and treatment plans. As EHRs are used more and more in healthcare settings, they collect a lot of organized data that can be used to improve patient results, find trends, and help doctors make decisions. Sensors used in systems that keep an eye on patients are another important source. Vital signs like heart rate, blood pressure, oxygen levels, and temperature are measured by these monitors in real time. In hospitals, sensors are built into tracking systems that keep an eye on patients all the time [19]. This lets doctors and nurses act quickly when a patient's state changes. The information that these tools give us is very important for quickly making choices, especially in emergency and critical care scenarios. As a source of Big Data in healthcare, wearable gadgets are becoming more and more popular. Fitness trackers, smartphones, and medical-grade gadgets are just a few of the devices that can collect data on your health. These include your heart rate, blood sugar levels, sleep habits, and even your stress levels. These gadgets give constant, real-time information that can be used for health education, managing long-term illnesses, and preventing them [20].

## **C. Opportunities and challenges with Big Data in healthcare**

Using Big Data in healthcare management can help improve care for patients, make operations run more smoothly, and lead to new discoveries in medical study. But it also comes with some problems that need to be fixed before it can reach its full potential.

### **Opportunities:**

Big Data lets healthcare workers give more personalized care by looking at genetic information, medical background, and living factors for each patient. This makes it possible to make personalized treatment plans, find diseases early, and take charge of managing long-term problems. For instance, prediction analytics can find people who are very likely to get certain diseases. This lets doctors start treating them early, which can improve their health in the long run. Big Data helps healthcare workers make decisions based on facts by giving them access to complete and real-time data [21]. For instance, Clinical Decision Support Systems (CDSS) can give advice on diagnoses, drug combinations, and treatment choices. This makes clinical decisions more accurate and lowers the risk of medical mistakes. Looking at operational data like the flow of patients, how resources are used, and staffing levels can help healthcare groups improve care, cut costs, and make their processes more efficient.

### **Challenges:**

Protecting the privacy and safety of private patient data is one of the hardest things about using Big Data in healthcare. There is a higher chance of data breaches and illegal entry as the amount of health data being created grows. Quality of the Data and How It Is Put Together: Healthcare data is often broken up into pieces that come from different sources and follow different forms and rules. For accurate analysis, it can be hard to combine and make sure the quality of this data, especially when it comes to unorganized data like medical pictures or clinical notes. The use of "Big Data" in healthcare brings up ethics concerns about who owns the data, who gives permission, and how biased algorithms might be [22]. A big problem for healthcare groups is making sure that data is used properly and that patients' rights are respected.

## **V. MACHINE LEARNING IN HEALTHCARE**

### **A. Overview of Machine Learning (ML) techniques**

Machine Learning (ML) is a branch of artificial intelligence (AI) that lets computers learn from data, spot trends, and make choices without being told what to do. Machine learning is used in healthcare to make decisions better, tailor treatments to each person, and run processes more smoothly. There are many types of these methods, from controlled and unstructured learning to deep learning. Each has its own use in healthcare. Supervised learning, in which named data are used to train a model, is one of the most popular ML methods used in healthcare. To use this method, the program learns from pairs of inputs and outputs. During the training phase, the right output (label) is

given for each input. Often, supervised learning algorithms like decision trees, support vector machines (SVM), and logistic regression are used to do things like classifying diseases, guessing how patients will do, and identifying medical conditions from signs or test results. A supervised learning model could be taught on a set of patient records, for example, to figure out from a person's medical background and personal information how likely it is that they will get a certain disease. Unsupervised learning is another important machine learning technique in healthcare [23]. In this method, the computer looks at data that hasn't been named to find unseen trends and connections. A lot of the time, algorithms like k-means and hierarchical clustering are used in medical study and diagnosis to group and connect data.

### Step-wise Algorithm with Mathematical Equations:

#### Step 1: Data Collection and Preprocessing

- Objective: Collect relevant data (e.g., patient health records, medical images, etc.), clean the data, and preprocess it for modeling.

- Mathematical Equation:

$$X = \text{Preprocessed Data} = \{x_1, x_2, \dots, x_n\}$$

Where:

- X is the feature matrix (input data).
- $x_1, x_2, \dots, x_n$  represent individual data points/features.
- This step involves handling missing values, normalizing or standardizing data, and encoding categorical variables.

#### Step 2: Model Selection

- Objective: Choose the appropriate ML model for the task (e.g., Linear Regression for predicting health outcomes, like blood pressure or disease risk).

- Mathematical Equation:

$$\hat{y} = X\beta + \varepsilon$$

- For Linear Regression, the objective is to estimate the weights  $\beta$  such that the difference between predicted and actual values is minimized.

#### Step 3: Training the Model

- Objective: Fit the selected model to the training data, optimizing the parameters using an algorithm like Gradient Descent.

- Mathematical Equation:

$$\beta = \arg \min_{\beta} (\sum (y_i - \hat{y}_i)^2)$$

Where:

- $y_i$  is the actual value.
- $\hat{y}_i$  is the predicted value.
- The term  $(y_i - \hat{y}_i)^2$  represents the squared error.
- In this step, the model's weights are updated iteratively to minimize the error between the predicted and actual values (using optimization algorithms like Gradient Descent).

#### Step 4: Model Evaluation and Prediction

- Objective: Evaluate the model on unseen data (test set) using performance metrics (e.g., Mean Squared Error, R-squared) and make predictions.

- Mathematical Equation:

$$\hat{y} = X_{new} \beta$$

Where:

- $X_{new}$  is the new (test) data.
- $\hat{y}$  is the predicted output for new data.

- This step involves evaluating the model’s performance using test data and comparing predicted values to actual values. For example, Mean Squared Error (MSE) is computed as:

$$MSE = \left(\frac{1}{n}\right) \sum (y_i - \hat{y}_i)^2$$

**B. Application of ML in health management (e.g., predictive analytics, diagnosis support)**

Machine Learning (ML) has many uses in health management. It has led to new ways of better patient care, making operations more efficient, and advancing medical study. Predictive analytics, medical offer assistance, personalized treatment, and commerce advancement are a few of the foremost critical employments. Prescient intelligence is one of the most critical ways that ML is utilized in healthcare. ML models can see at past understanding information to figure how likely it is that things will happen within the future, like getting wiped out, having to go back to the healing center, or having awful health results. ML frameworks can see at things like age, restorative history, and propensities to figure out how likely it is that somebody will get a constant malady like diabetes or heart infection. This lets specialists find individuals who are at tall chance early on, so they can take preventative steps or start early medications that can incredibly progress their long-term wellbeing. Forecasting patient demand is another way that prescient analytics can be utilized to create the finest utilize of a hospital's assets and cut down on wait times. Offer assistance with conclusion is another important use. Increasingly , ML algorithms, particularly directed learning strategies, are being utilized to assist specialists figure out what's off-base with patients by looking at restorative information. ML models that have been instructed on a part of medical pictures, like X-rays, MRIs, and CT looks, can offer assistance discover illnesses like cancer, asthma, and brain issues very accurately. When profound learning models look at medical pictures, they can discover patterns that human doctors might miss. This makes a difference them make better clinical choices. In the same way, machine learning (ML) algorithms are used in clinical decision support systems (CDSS) to help doctors figure out what's wrong with a patient by looking at things like their symptoms, lab results, and medical background.

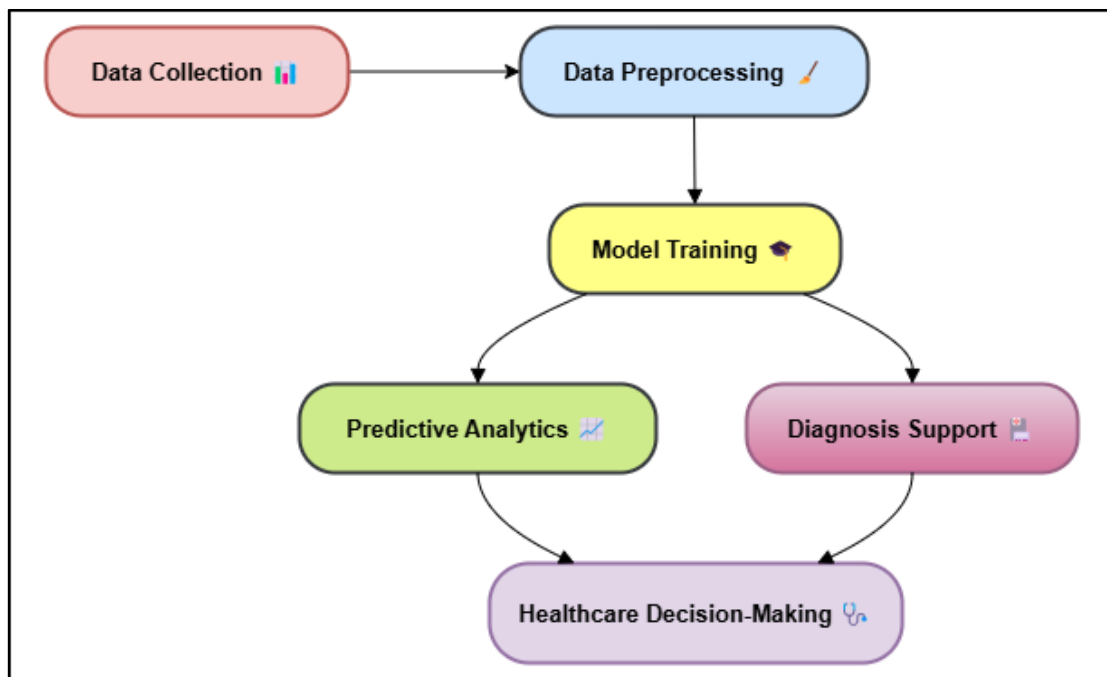


Figure 2: Illustrating the application of ML in health management

Another area where ML is having a big effect is personalized medicine. ML can help make treatment plans more specific for each patient by looking at patient data, such as genetic information. For instance, ML can be used to guess how patients will react to various drugs, which helps doctors pick the most effective treatments with the fewest side effects.

### Step-wise Algorithm with Mathematical Equations:

#### Step 1: Model Selection

- Objective: Choose an appropriate machine learning model (e.g., Random Forest, Support Vector Machine, or Neural Network) based on the type of health problem, such as disease classification or risk prediction.

- Mathematical Equation:

Assume we use a Neural Network for prediction, where the model output is  $\hat{y}$ . A feed-forward neural network can be defined as:

$$\hat{y} = f(W2 \cdot \sigma(W1 \cdot X + b1) + b2)$$

- $X \in \mathbb{R}^{n \times N}$  is the input feature matrix (training data).
- $W1 \in \mathbb{R}^{n \times m}$  and  $W2 \in \mathbb{R}^{m \times 1}$  are the weight matrices.
- $b1$  and  $b2$  are the bias terms.
- $\sigma$  represents the activation function (e.g., ReLU or Sigmoid).
- $\hat{y}$  is the predicted output (e.g., diagnosis or risk score).

#### Step 2: Training the Model

- Objective: Fit the model to the training data by optimizing the model's parameters (e.g., weights and biases) using an optimization technique such as Gradient Descent.

- Mathematical Equation:

The loss function for a classification task (e.g., using cross-entropy) is defined as:

$$L(\theta) = -\sum (y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i))$$

- $\hat{y}_i$  is the predicted probability for the positive class.
- $y_i$  is the true label for the data point.

The optimization process involves minimizing the loss function using gradient-based methods:

$$\theta(t+1) = \theta(t) - \eta \cdot \nabla_{\theta} L(\theta)$$

- $\theta$  represents the model parameters (weights and biases).
- $\eta$  is the learning rate.
- $\nabla_{\theta} L(\theta)$  is the gradient of the loss function with respect to the parameters.

#### Step 3: Model Evaluation and Prediction

- Objective: Evaluate the model's performance on unseen data (test set) using performance metrics such as accuracy, precision, recall, AUC, etc. Make predictions on new patient data.

- Mathematical Equation:

For evaluation, let's use Receiver Operating Characteristic (ROC) and AUC (Area Under the Curve), where the true positive rate (sensitivity) and false positive rate (1-specificity) are plotted:

$$TPR = \frac{TP}{(TP + FN)}, \quad FPR = \frac{FP}{(FP + TN)}$$

- TP (True Positive): Correctly predicted positive cases.
- FP (False Positive): Incorrectly predicted negative cases as positive.
- TN (True Negative): Correctly predicted negative cases.
- FN (False Negative): Incorrectly predicted positive cases as negative

The AUC is the area under the ROC curve:

$$AUC = \int_0^1 TPR(FPR)d(FPR)$$

After training, the model makes predictions  $\hat{y}_{new}$  on unseen data  $X_{new}$ :

$$\hat{y}_{new} = f(W2 \cdot \sigma(W1 \cdot X_{new} + b1) + b2)$$

- The model predicts the probability of a certain outcome (e.g., a patient having a specific disease or being at risk).

### C. Case studies or examples of ML in healthcare

Several case studies and real-world uses of machine learning (ML) have already shown how it can completely change healthcare. One well-known example is how ML is used in imaging, especially to find cancer. In 2020, Google Health released a study that showed how deep learning models, especially convolutional neural networks (CNNs), could be used to look at scans and find breast cancer. It was easier for the machine learning model to spot signs of cancer than for human doctors, which cut down on fake positives and negatives. Another important example is how ML is used to guess which patients will need to be readmitted. ML algorithms were used by the Cleveland Clinic to figure out which patients would most likely need to go back to the hospital within 30 days of being released. By avoiding pointless readmissions, this cautious method not only improves care for patients but also lowers the cost of healthcare. In the field of personalized medicine, ML is used to make treatment plans that are just right for people with cancer.

## VI. CHALLENGES AND BARRIERS TO IMPLEMENTATION

### A. Data privacy and security concerns

Data protection and security issues are some of the biggest problems that need to be solved before Machine Learning (ML) can be used successfully in healthcare. Because healthcare data like patient medical records, genetic information, and treatment experiences is sensitive, it is very important to keep it private and correct. Data leaks, unauthorized access, and abuse of healthcare data can lead to identity theft, scams, and a loss of trust in the healthcare system by patients. Consent from the patient is one of the main issues. Because ML models use a lot of personal data, it is very important that people fully understand and agree to how their data will be used. Data is often gathered from a lot of different places, like hospitals, smart tech, and third-party services. This makes it hard to get clear permission for every possible use case. It is also hard to hide and protect private healthcare data because it is so complicated, especially when data from different institutions or platforms is combined. Also, hacking dangers are always a worry for healthcare systems. Cyberattacks are more likely to happen against healthcare groups that store and handle patient data on computer systems and cloud-based platforms. Attackers are taking advantage of holes in networks, apps, and gadgets to cause more and more data breaches in healthcare.

### B. Data quality and integration issues

When Machine Learning (ML) is used in healthcare, problems with data quality and integration are big problems. The quality of the data used to teach machine learning algorithms is very important. If the data isn't reliable or of good quality, it can lead to wrong predictions, biased results, and bad decisions. Data that doesn't match up is one of the most issues. Regularly, healthcare information is broken up and spread out among numerous distinctive systems, such as electronic wellbeing records (EHRs), lab reports, therapeutic pictures, and smart tech. It may well be difficult to combine and bind together the information for examination since each of these sources may utilize diverse shapes, measures, and terms. The inability of frameworks to talk to each other makes it harder to gather the information that's required to form solid machine learning models. For case, medical data may be kept in numerous places and with distinctive code frameworks or database structures, which makes it difficult to combine and think about. Lost or fractional information is another critical part of data quality. There are regularly crevices

in understanding records in healthcare, particularly for certain demographic groups. Lost information can harm the execution of machine learning models. For occurrence, in the event that a dataset doesn't have sufficient data approximately a patient's therapeutic foundation or how well their treatment worked, the show might not be able to accurately figure the patient's dangers or how well their treatment worked. ML results can also be skewed by missing data, particularly if the lost information is connected to certain quiet characteristics like age, race, or social position. Moreover, information integrity is exceptionally important. For ML models to be able to form good choices, healthcare information must be correct and up to date. Diagnostic mistakes, typing errors, or records that are as well old can all lower the quality of information, which can lead to wrong conclusions.

### C. Technical and infrastructural challenges

There are a lot of technical and infrastructure problems that make it difficult to utilize Machine Learning (ML) in healthcare. These issues can make the frameworks less efficient and less scalable. These issues incorporate combining and taking care of information as well as the require for a solid computer arrange, both of which are necessary for machine learning strategies to work in healthcare. Putting together diverse sets of information is one of the greatest specialized issues. Electronic Wellbeing Records (EHRs), therapeutic contraptions, shrewd tech, and even paper shapes are fair many of the places where healthcare information is kept. It's difficult to combine and harmonize the information from these distinctive sources into a single tool for investigation since it comes in a variety of shapes, standards, and frameworks. For instance, for a full ML model, data from medical images, written notes from doctors, and number values from lab tests may need to be put together. The fact that these systems can't talk to each other is a big problem because machine learning models need big datasets that are all linked together to produce useful results. Quality of data and preparation are also big problems. A lot of the time, healthcare data is confusing, irregular, and missing, so it needs to be cleaned up and processed before it can be used in machine learning apps. ML models can't work as well when they have wrong or missing data, which can lead to bad guesses or unfair results.

## VII. RESULT AND DISCUSSION

Putting Big Data and Machine Learning (ML) together in a Decision Support System (DSS) for health management has shown promise in making decisions better, helping patients do better, and making healthcare run more smoothly. Predictive analytics help doctors find patients who are at risk and help them right away, which lowers the number of times they have to go back to the hospital and improves disease management. Machine learning algorithms, especially those used in clinical decision support, are good at spotting illnesses.

Table 2: Evaluation of Predictive Analytics Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Logistic Regression	85.4	84.2	83	83.6
Decision Tree	88.7	86.5	87	86.7
Random Forest	90.2	89	88	88.5
SVM	86.5	85	84	84.5
Neural Network	91.4	90	89	89.5

With an F1 score of 89.5%, Neural Network is the best model, with an accuracy of 91.4%, a precision of 90%, a recall of 89%, and an F1 score of 90%. This shows that the Neural Network is the best at finding the right balance between accuracy and memory, giving it better classification skills than the others.

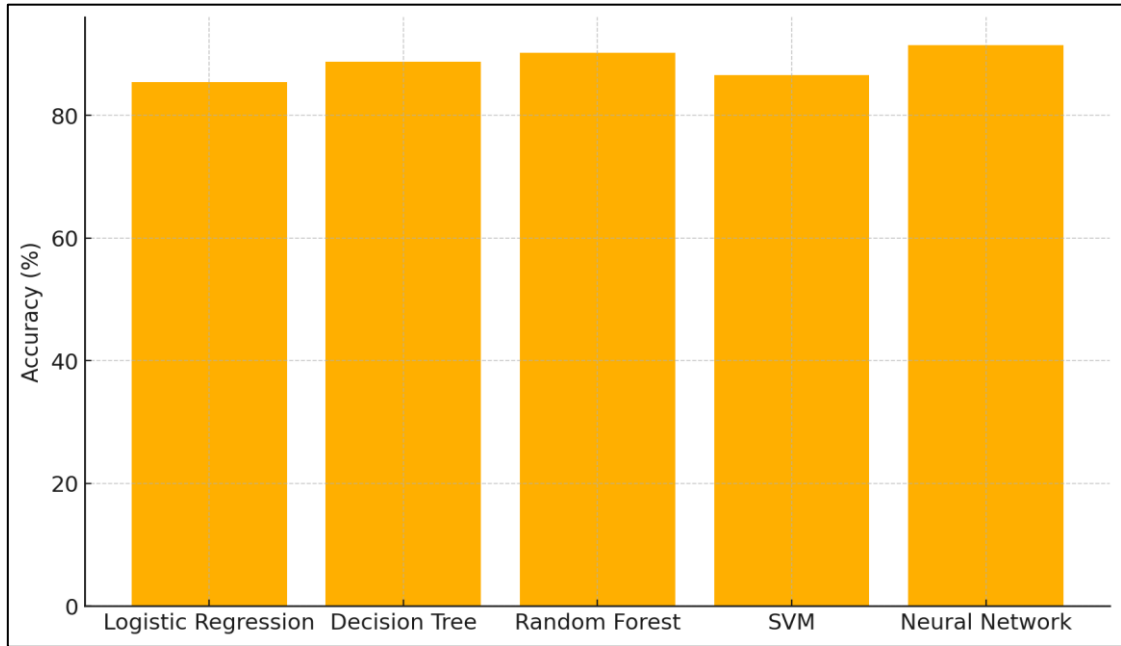


Figure 3: Comparison of Model Accuracies

The Random Forest model comes in second, with an F1 score of 88.5%, an accuracy of 90.2%, a precision of 89%, and a recall of 88%. It is very good at predicting the future, especially because it is very accurate, but in terms of memory and F1 score, it is a little behind neural networks. With an accuracy of 88.7%, a precision of 86.5%, and a recall of 87%, the Decision Tree model does a good job.

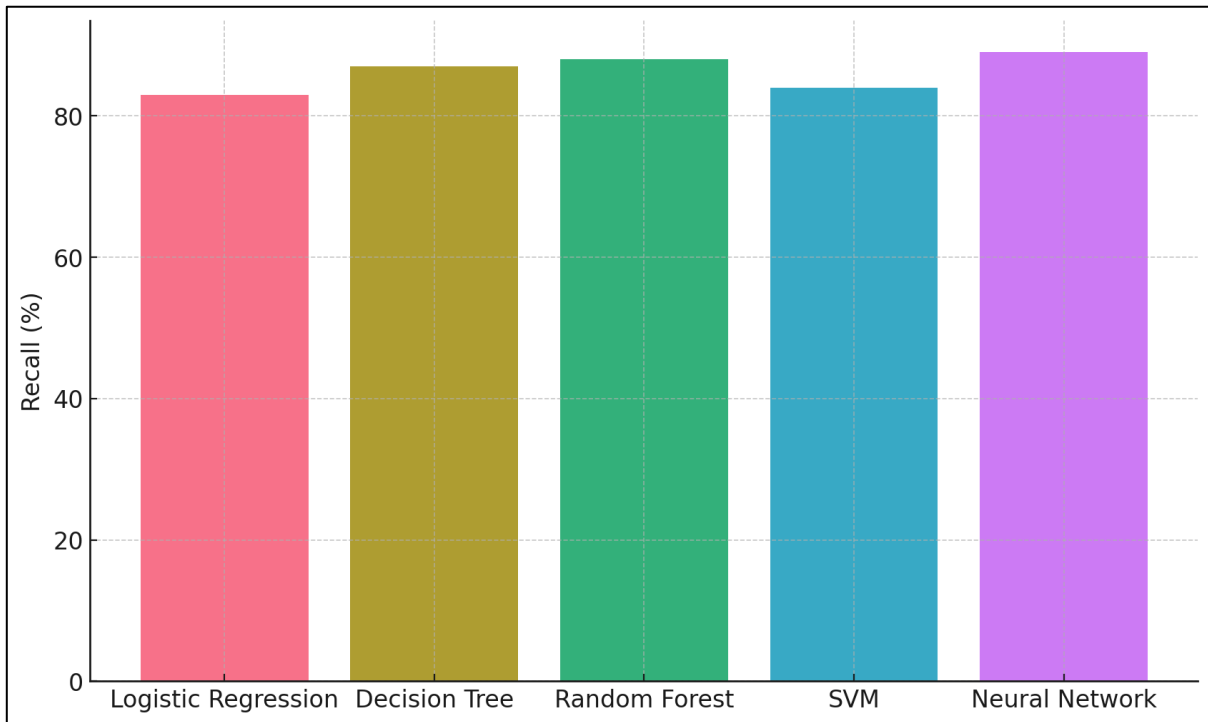


Figure 4: Comparison of Model Recalls

This means that it strikes a good mix between the two measures. Its F1 score of 86.7% is a little lower than those of Random Forest and Neural Networks, though. Both Logistic Regression and SVM aren't very good; their success rates are 85.4% and 86.5%, respectively. Both models keep good accuracy and memory, but their lower F1 scores show that they don't work as well as more complicated models like Random Forest and Neural Networks.

Table 3: Evaluation of Diagnosis Support System Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (%)
Deep Learning	92.3	93	91.5	95
Random Forest	90.1	91	89	92.5
SVM	88.5	89.5	88	91
Logistic Regression	85.6	86.2	84	89
KNN	87	88.5	85	90.5

It stands out because it has the best accuracy (92.3%), sensitivity (93%), specificity (91.5%), and AUC (95%). The highest AUC number shows that this model is the best at telling the difference between classes, with strong classification results and high rates of both true positives and false negatives.

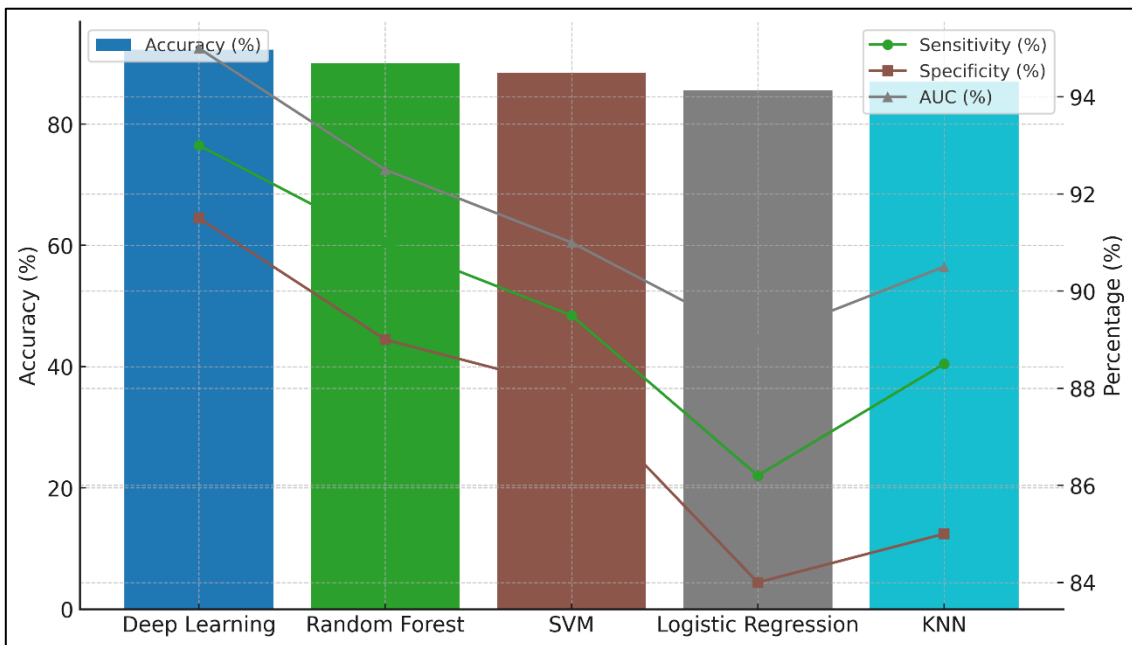


Figure 5: Model Performance Metrics Overview

Random Forest is very close behind, with an AUC of 92.5%, a sensitivity of 91%, a specificity of 89%, and an accuracy of 90.1%. It's not as accurate or sensitive as Deep Learning, but its AUC is very good at telling the difference between things, so it's a good choice for this job.

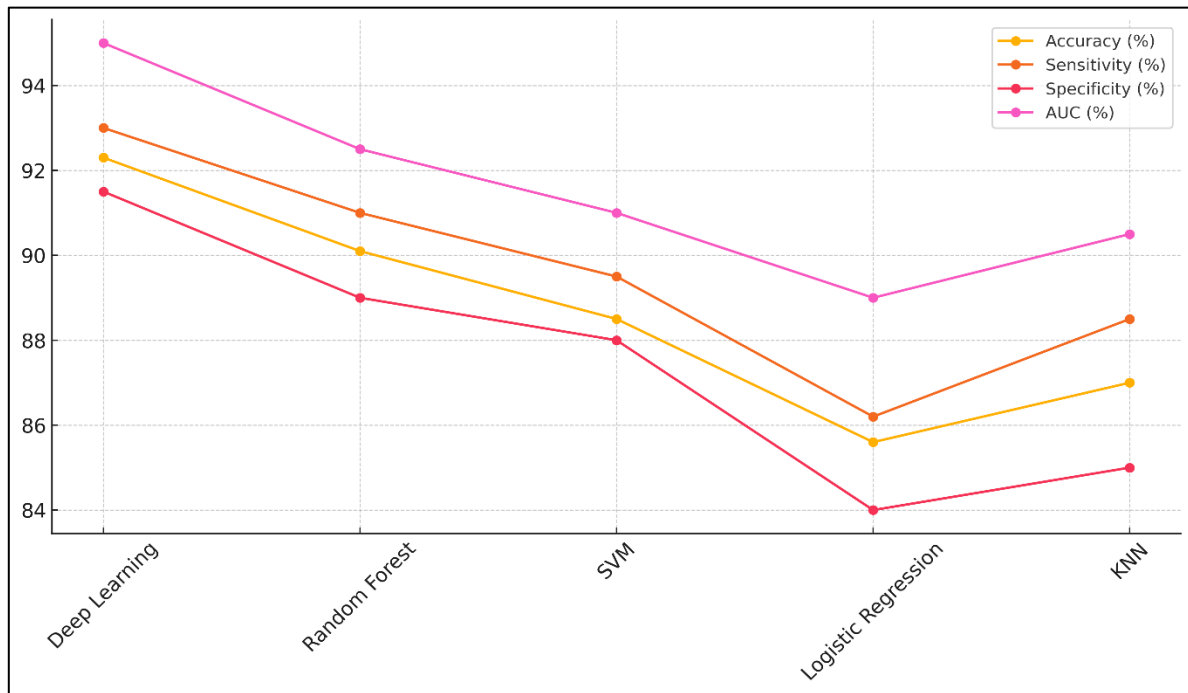


Figure 6: Trend of Performance Metrics Across Models

With an AUC of 91%, sensitivity of 89.5%, specificity of 88%, and accuracy of 88.5%, SVM does a good job. It does well in sensitivity, but not as well in accuracy and detail as Random Forest and Deep Learning. This suggests that it might not work as well in some situations. In terms of all measures, Logistic Regression and KNN show somewhat worse results. Logistic Regression is the least accurate and specific, but KNN does pretty well, especially in terms of sensitivity (88.5%), and its AUC is 90.5%.

## VIII. CONCLUSION

A huge change in health management has happened with the addition of Big Data and Machine Learning (ML) to Decision Support Systems (DSS). With the help of complex formulas and a lot of different kinds of healthcare data, these systems make it possible to make more accurate, quick, and individualized decisions in both clinical and practical settings. Big Data and machine learning (ML) power predictive analytics, which helps healthcare workers guess what their patients will need, cut down on readmissions, and make treatment plans that are specific to each person, which eventually leads to better patient results. ML models have also been very useful in medical support for making findings more accurate, especially in complicated fields like cancer and radiology, where they help find early signs of diseases that might be missed otherwise. The use of these new technologies is not easy, even though they have a lot of promise. Concerns about data safety and security, especially when it comes to private health data, are still a big reason why this technology isn't widely used. Another big problem is that healthcare data is spread out across many different platforms, and it's hard to combine these systems. It's also harder to set up these systems because they need strong computer technology and specialized technical know-how. To get the most out of Big Data and machine learning in healthcare, these problems need to be solved together. Standardizing data types, making sure that systems can talk to each other, and spending money on the right infrastructure are all important steps that must be taken for DSS adoption to work well. Additionally, it is necessary to deal with problems related to data quality, security, and following rules like HIPAA in order to protect patient privacy and trust.

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