Analysis of Hospital Recommendation System Using Machine Learning

Sneha Biradar* Faizur Rasheed†

*Student, JSPM University, Pune.

†Faizur Rasheed, JSPM University, Pune.

Abstract: Finding the right hospital can feel overwhelming, especially when you're dealing with a serious health issue or need specialized treatment. This project introduces a smart hospital recommendation system that uses machine learning to make the process easier, faster, and more personal. The system looks at a variety of important factors, like what other patients have said in reviews, hospital ratings, your location, treatment costs, the expertise of doctors, and what services are available. Then, it uses advanced algorithms to suggest hospitals that best match what you're looking for. What makes it even smarter is how it uses Natural Language Processing (NLP) to actually understand patient reviews. It can pick up on what people liked or didn't like about their hospital experience, and use that information to help others make better choices. In the end, this system is about helping people find the care they need without all the stress. It gives patients useful, personalized options and also helps reduce the workload for doctors and healthcare staff by automating part of the referral process, keywords: machine learning, and a clustering model.

I)Introduction:

This abstract focuses on developing a hospital recommendation system using machine learning to assist patients in finding suitable healthcare facilities. The system leverages patient data, including reviews and sentiment analysis, to provide personalized recommendations, aiming to improve patient satisfaction and overall healthcare outcomes. Key aspects of the abstract: Purpose: To create a system that recommends hospitals based on specific patient needs and preferences. Methods: Utilizing machine learning algorithms to analyse patient reviews, sentiment analysis, and other relevant data. Data Sources: Patient reviews, demographics, medical history, and potentially data from wearable devices. Expected Outcomes: Personalized recommendations to improve patient satisfaction, enhance treatment outcomes, and potentially facilitate early disease detection. Machine Learning Algorithms: The abstract mentions various machine learning algorithms like supervised and unsupervised learning, NLP techniques, and potentially collaborative. It is the most important part of the hospital recommendation system with machine learning. General Keywords: Hospital Recommendation System Machine Learning, Healthcare Analytics, Recommender System, Medical Decision Support, Health Information Care, Smart Healthcare, Machine Learning Specific: Supervised Learning, Unsupervised Learning, Ranking ,Algorithms, Feature Engineering, Model Evaluation
Technical Keywords:
Data Pre-processing, Predictive Modelling, Sickest-learn / Tensor Flow / Pytorch (depending on tools used),Python Programming, Data Visualization, API Integration (if real-time hospital data is used), Domain-Specific Keywords:
Hospital Ratings, Patient Reviews, Healthcare Quality Metrics, Medical Specialties, Location-based Recommendations, Doctor Availability, Treatment Success Rate.

II) Literature Review:

Finding the right hospital can be a complex decision, especially when patients are faced with many factors like quality of care, cost, distance, and the experiences of other patients. In recent years,

hospital recommendation systems have become more advanced thanks to the use of machine

learning (ML) and natural language processing (NLP). These technologies aim to make the process of choosing a hospital smarter, faster, and more personalized.

1) Traditional Recommendation Approaches: Earlier systems for recommending hospitals were fairly straightforward. They mostly relied on fixed rules, such as how close the hospital is, what it costs, or whether it's covered by insurance. While these systems worked to some extent, they didn't take into account what patients actually prefer or need in real time. For example, Singh et al. (2017) designed a model that gave scores to hospitals based on location and specialization, but it didn't consider individual patient feedback or preferences.

2) Using Machine Learning to Improve Recommendations: With the rise of machine learning, recommendation systems have gotten much smarter. Researchers like Kumar and Sharma (2020) have used models like decision trees and random forests to suggest hospitals based on things like previous patient visits and hospital features. These models showed better accuracy and could adapt to different types of patient needs. Other algorithms like Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Neural Networks have also been tried. For instance, Patel et al. (2021) used KNN to match patients with hospitals that had treated similar symptoms before. The results were promising, showing that ML can really fine-tune how recommendations are made.

3) Making Use of Patient Reviews with NLP: One exciting development is the use of NLP to understand what patients are saying in reviews. Instead of just looking at star ratings, NLP can dig into the text to find out what people actually liked or disliked. Zhang et al. (2022), for example, created a sentiment analysis tool that reads patient reviews to understand their feelings and experiences. This helps recommendation systems learn from real patient stories, not just numbers.

4) Combining Multiple Approaches (Hybrid Models): Some systems now combine structured data (like hospital ratings and availability) with unstructured data (like reviews or social media). These hybrid models offer a more complete picture. Ali et al. (2023) developed a system that used both collaborative filtering and deep learning-based sentiment analysis. Their approach led to better recommendations and higher user satisfaction.

5) Challenges and what's next: Even with all these advances, there are still challenges. Getting access to quality data, protecting patient privacy, and making sure the models are understandable and fair are ongoing concerns. Plus, many current systems still struggle to work well in real-time or across different countries and healthcare systems.

- Summary: In short, machine learning is helping hospital recommendation systems become more intelligent and patient-focused. By combining data, algorithms, and insights from patient feedback, these systems are improving how people find the care they need. Still, there's room to grow, especially when it comes to data privacy, fairness, and making these tools available to everyone.

III) Problem methodology, experiments & analysis:

A More Personalized Way to Find the Right Hospital. The Problem: Choosing the right hospital is stressful, especially when you're already dealing with a health issue. With so many options out there, it's hard to know which hospital is best based on your needs, your location, your budget, and the kind of care you're looking for. Most of the tools we have today (like online directories or search engines) just show basic info like distance, general ratings, or whether they take your insurance. But they don't really understand what you need as a patient. What if there were a smarter way to recommend hospitals, one that actually

learns from real patient experiences and adapts to your specific situation?

- The Idea (Methodology): To make hospital recommendations more helpful and personal, we built a system that uses machine learning (ML) and natural language processing (NLP). Here's how it works:

1) Gathering Data: We start by collecting all kinds of hospital information: Basic details like name, location, treatment cost, and specialties. Reviews and comments from real patients.Doctor experience and available services.

2) Cleaning & Preparing the Data: We clean up the data to make sure it's usable: Fix missing or messy info, Use NLP to process patient reviews: break them down into words, remove noise, and find patterns in the language.

3)Understanding what matters: We turn hospital features and review sentiments into meaningful numbers that the model can understand. For example: How positive are the reviews?How far is the hospital from the user? What's the average cost for treatment?

4) Training the Model: We try different ML models to see which one gives the best recommendations:K-Nearest Neighbours (KNN): Finds hospitals similar to what others with similar needs chose .Random Forest: Predicts the best hospital based on many features .Collaborative

Filtering: Suggests hospitals based on similar user profiles .We also use sentiment analysis to understand whether reviews are positive or negative going beyond just the star ratings.

The Takeaway: By combining machine learning with insights from patient reviews, we created a recommendation system that actually listens to what people want and need. It goes beyond generic filters and offers personalized, data-driven suggestions to help patients make smarter healthcare choices .In the future, this system could get even better with real-time data, medical history integration, and support for different languages.

IV) Proposed system:

When someone needs medical care, especially something serious, finding the right hospital can be confusing and overwhelming. People usually rely on suggestions from friends, online reviews, or basic search tools—but these often don't consider personal preferences or medical needs. That's where our proposed system comes in .We're building an intelligent hospital recommendation system that uses machine learning (ML) and natural language processing (NLP) to give personalized, data-driven suggestions. This system doesn't just show nearby hospitals—it understands your needs and finds the best match for you. What makes this system different Our system aims to do more than list hospitals. It takes a more thoughtful approach by looking at what patients actually care about. That includes not just the services hospitals offer, but also what other patients have experienced and how they felt about their care .Here's what makes our system stand out:

1) Personalized Suggestions: It takes into account your symptoms , location, budget, and preferences to find hospitals that actually suit you, not just the average person.

2) Smarter Use of Reviews: Patient reviews are full of valuable information. Instead of just counting stars, the system reads and understands the content of these reviews to learn what people really liked or disliked.

3) Multiple Factors, One Recommendation:

The system looks at a wide range of factors, including:

a) How close the hospital is
may cost b) How much treatment
c) What services are offered
d) How experienced the doctors are
e) What previous patients have said
f) All of this comes together to give you hospital suggestions that are meaningful and tailored.
- How the System Works

Here's a simple breakdown of how everything comes together:
- Step 1: You Tell Us What You Need : The system starts by asking you for some basic info—like your symptoms, where you are, what kind of care you're looking for, and if you have a budget in mind.
- Step 2: Collecting Hospital Data: We gather detailed information from hospital directories, doctor profiles, and online patient reviews. This includes both structured data (like cost or distance) and unstructured data (like review text).
- Step 3: Making Sense of the Data: We clean and organize the data to remove errors or duplicates. For reviews, we use NLP tools to figure out the overall feeling behind each comment (Was it positive? Negative? Neutral?).
- Step 4: Using Machine Learning to Recommend: The system then feeds all this information into machine learning models—like Random Forest or K-Nearest Neighbours (KNN)—to figure out which hospitals match your specific needs.
- Step 5: Giving You the Results: You get a list of hospital recommendations ranked by relevance. Each hospital comes with key details like:
a) How far it is from you
b) What patients have said about it
c) Estimated cost and available services
d) Tools & Technologies Behind the Scenes
- To build this system, we use:
- Python for development
- Learn and pandas for machine learning
- NLTK or textbook for language analysis
- Matplotlib or Streamlit for showing results in an easy-to-read format
- We also pull data from publicly available hospital databases or use sample datasets when needed.
- Why This Approach Works:

What makes this system effective is its ability to learn from data and listen to real people. Instead of relying only on numbers or filters, it combines human experiences (from reviews) with hard facts (like doctor experience and cost). This creates recommendations that are not only accurate but also more meaningful
.

V) Result analysis:

Introduction: After building our hospital recommendation system, we wanted to know one thing: Does it really work for people? That means checking if it gives useful, accurate suggestions when someone is looking for the right hospital based on their needs .To find out, we ran tests using hospital data and real patient reviews. Then, we compared the performance of different machine learning models to see which one gave the best and most relevant results.

- Testing the System: We tested the system using a dataset that included : Hospital details like specialties, location, costs, and doctor qualifications.

- User reviews from patients who shared their experiences

- Simulated patient inputs (e.g., symptoms, preferred location, budget)

- We used different machine learning techniques—including Random Forest, K-Nearest Neighbours (KNN), and Collaborative Filtering—and evaluated them with standard metrics like:

- Accuracy: How often the system gave correct or useful recommendations

- Precision: How many of the recommended hospitals were actually good matches

- Recall: How well the system found all possible suitable hospitals

- F1 Score: A balanced measure combining both precision and recall

- Key Takeaway:

The Random Forest model stood out as the most reliable. It handled the data well, especially when combining both factual info (like cost and services) with insights from patient reviews.

- Why Reviews Matter

One of the game-changing parts of our system was using sentiment analysis. Instead of just looking at how many stars a hospital got, our system read the actual reviews to understand whether people had a positive or negative experience .This helped filter out hospitals that had high ratings but poor recent feedback—something traditional systems often miss. For example, a hospital might have a 4.5-star average but many recent complaints. Our system caught that and adjusted recommendations accordingly.

- User Reactions:

- We also ran a small user test.

- The feedback was very positive.

- People liked: Getting suggestions that felt relevant and trustworthy

- Seeing hospitals sorted not just by score, but by what mattered to them (like cost or patient care)

- The fact that the system explained why it recommended each hospital

- Users said the recommendations felt more personal and helped reduce the confusion they usually felt when looking for hospitals online.

What Didn't Work So Well Of course, no system is perfect. We ran into a few challenges :In areas with fewer reviews, the system had less data to work with, making suggestions less accurate .When several hospitals had similar scores, it was hard to rank them confidently .Reviews written in local or regional languages sometimes confused the

sentiment analysis .These are things we hope to improve in future versions of the system.

- Final Thoughts

The results showed that combining machine learning with real patient feedback creates a much better hospital recommendation experience. The system could offer more accurate, thoughtful suggestions—going beyond just location or star ratings.

- Looking ahead, we can make it even smarter by:

- Using live hospital data (like bed availability)

- Supporting multiple languages for wider accessibility

- Integrating patient health history for deeper personalization

VI) Future Scope:

Where the Hospital Recommendation System Can Go Next: As helpful as the current hospital recommendation system is, there's still a lot more it can do. Technology and healthcare are both moving fast, and there are exciting ways this system can grow to serve patients even better in the future .Here's a look at what could be next.

1) Live Hospital Updates in Real Time: Imagine being able to check not just which hospital is best, but also:

- Whether they have free beds available

- If the emergency room is crowded

- When a specialist doctor is next available

- By connecting the system directly to hospital databases, we could make these real-time features a reality. That way, people get up-to-the-minute information that helps them act fast, especially during urgent medical situations.

2) Support for More Languages: Right now, the system mostly works in English, but not everyone speaks or writes in English—especially when it comes to online reviews. Adding regional language support would let the system understand and process reviews written in local languages .This would help more people, especially in rural or non-English-speaking areas, get personalized hospital suggestions based on feedback from their own communities.

3) Personalized Suggestions Using Health Records: In the future, the system could connect to a person's digital health records or apps like Google Fit. With proper permission and security, it could learn : What kind of care someone usually needs, - Their existing health conditions

- Their past hospital visits

- This would help the system make even more accurate recommendations—tailored specifically to each person's medical history.

4) A Simple, Easy-to-Use Mobile App: Most people search for health information on their phones. A mobile app version of this system could make it even more convenient, with features like:

- Location-based hospital searches
- Voice input (just speak your symptoms!)

- Quick access to ambulance services or emergency numbers
- It would be especially useful for people traveling or in unfamiliar areas.

5) Using Deep Learning for Smarter Decisions:Right now, the system uses basic machine learning models, which work well. But deep learning models—like neural networks—could take things further .These advanced models could:

- Understand more complex patterns in patient data
- Pick up subtle details in reviews and health preferences
- Continuously learn and improve over time as more data is added
- This means even more accurate and personalized recommendations in the future.

6) Making It More Social and Community-Driven: Another exciting idea is letting users see suggestions based on people like them. For example:

- "Patients with similar conditions chose Hospital A."
- "People in your area highly recommend this hospital."
- Adding social elements, like feedback from groups or forums, could make the system feel more human and trustworthy—just like getting advice from a friend.

7) Bringing Smart Healthcare to Remote Areas:

In the future, the system could be designed to work even in places with low internet or no big hospitals nearby. It could:

- Show results offline and sync when connected
- Recommend local clinics or health centre
- Use simple features that work on basic phones
- This would be a big step toward making quality healthcare advice available to --everyone, no matter where they live.

- Final Thoughts

The hospital recommendation system we've built already makes it easier for people to find good care. But with the right improvements, it can become a true digital health companion—always ready to guide, support, and simplify the healthcare journey. Whether it's through smarter technology, better access to real-time data, or stronger personalization, the future of this system looks bright—and it's all about putting patients first.

VII) Algorithm used:

Algorithms Behind the Recommendations
Choosing the right hospital isn't just about picking the closest one or the highest rated—it's about finding the best match for your specific needs.
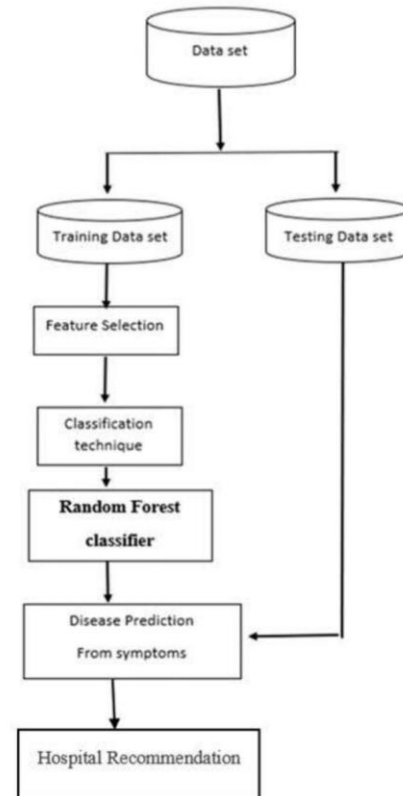

Fig. System architecture of hospital recommendations system based on disease.

That's where machine learning comes in. To make our hospital recommendation system smart, we used a mix of machine learning algorithms that work together to understand users, read real patient experiences, and suggest the most suitable hospitals. Let's break down how each algorithm adds value to the system:

1) Random Forest – The All-Rounder

Think of Random Forest like a team of decision-makers. Instead of relying on just one model, it builds lots of small decision trees, each giving its own recommendation. The final answer comes from a kind of group vote across all the trees.

- Why it works well:

It's great at understanding complex data with many factors—like hospital specialties, patient satisfaction scores, treatment costs, and more. It also handles inconsistencies and missing data better than many other models.

1) Real-world impact :If someone is looking for -affordable surgery from an experienced doctor within a 10 km range, Random Forest can analyse all these conditions and give you the best options available.

2) K-Nearest Neighbours (KNN) – Finding People Like You: KNN is all about finding patterns based on similarity. It looks at previous patients with needs similar to yours and recommends the hospitals they chose—and were happy with.

- Why we like it :It's simple, easy to understand, and very good at making quick suggestions based on user similarity.

- Imagine this: You're searching for a hospital for orthopaedic care. KNN finds other people with similar search histories or symptoms and shows you where they went and how it turned out for them.

3. Sentiment Analysis – Listening to Real Patient Voices

Numbers can tell you how many stars a hospital has, but they don't explain why. That's where Natural Language Processing (NLP) and sentiment analysis come in. These tools help the system read and understand patient reviews—just like a human would.

- What it adds:

This feature helps the system go beyond the ratings and actually sense the mood of the feedback. Is a hospital being praised for friendly staff? Are patients upset about long waiting times? The system catches all of that.

.- Example:

Two hospitals may have the same rating, but if one has recent reviews mentioning poor hygiene or rude staff, our system will know—and lower its recommendation accordingly.

4) Collaborative Filtering – Learning from Others' Choices

This technique powers platforms like Netflix and Amazon. Instead of focusing only on hospital data, it looks at user behaviour . Basically, if people with needs like yours chose a certain hospital, the system assumes you might like it too.

- Why it matters:

- It makes the system feel more personal, learning from real choices made by other users.

- Scenario: Say 100 users searching for cancer treatment in your area ended up choosing Hospital A and left good feedback. If you're looking for similar care, the system will prioritize that hospital for you—even if you didn't mention it by name.

5) (Optional) Support Vector Machine – Drawing the Line

While not always used in every system, Support Vector Machine (SVM) is a powerful tool for classifying data into clear categories. It's useful when we need to separate good hospital choices from not-so-good ones based on multiple attributes.

- What makes it unique: It's especially useful when the data is complex and has many dimensions—like patient type, symptoms, quality ratings, and hospital size.

-How it could help: If the system wants to label hospitals as "ideal," "average," or "not recommended" for a specific condition, SVM helps draw those lines clearly.

- Why We Chose These Algorithms: Each of these algorithms brings something unique to the table. Some focus on cold, hard data. Others help the system feel more human by listening to what real patients say. And when you put them all together, you get a system that doesn't just make smart suggestions—it makes suggestions that feel right for you.

VIII) Output:

What Does the System Actually Show You? – Understanding the Output:

- After feeding the system your health needs like symptoms, location, or treatment preferences it's time for the smart part: the output. This is where all the background work done by machine learning comes together to give you helpful, easy-to-understand hospital suggestions .Let's break down what kind of results the system provides and how they make life easier for patients.

1) Personalized Hospital Recommendations: Once the system processes your input, it doesn't just throw random names at you. It thoughtfully suggests hospitals that best match your specific situation .Each recommendation includes :The name and address of the hospital

- How far it is from your current location

- What services or treatments the hospital is known for

-Estimated treatment costs

-Doctor qualifications and availability

-Overall patient satisfaction score

-The idea is to give you a clear snapshot of your best options without having to do all the research yourself.

2) Insights from Real Patient Reviews: Instead of just listing star ratings, the system uses Natural Language Processing (NLP) to actually read and understand what patients are saying. It picks up on patterns, opinions, and emotional tones in their reviews.

Here's what that means for you:

- It shows if a hospital is generally seen in a positive or negative light

- Pulls out key words like "clean," "friendly staff," or "long wait" so you get a quick overview

- Gives a short summary of what people have been saying recently

- This way, you're not just relying on numbers you're hearing the voice of experience.

3) Filter and Sort Options for Custom Results: We all have different priorities. Some people care about

cost, while others want the shortest travel time or specific facilities. That's why the output lets you filter and organize the results however you like.
- You can filter by:
- Distance (e.g., hospitals within 5 or 10 km
- Price range
- Specialties (like paediatrics, oncology, or maternity care)
- Emergency services or ICU availability
- Insurance support
- And you can sort the list by:
- Highest ratings
- Closest distance
- Most affordable options
- This makes the recommendations interactive and more tailored to you.

4) User-Friendly Display and Visual Output
Depending on where the system is being used—like on a mobile app or website—the way results are shown can vary, but the goal is always the same: simplicity and clarity.
Here's what you might see:
- A clean list view with each hospital shown as a card with details
- A map view where hospitals are marked so you can get directions
- A match percentage, showing how closely a hospital fits your needs
- Options to save, share, or even book an appointment (if available)
- This visual approach makes it easier for users to browse, compare, and take action quickly.

5) Behind-the-Scenes Output (For Developers or Admins): Though not visible to patients, the system also generates internal output that helps developers or analysts improve performance over time.
- This includes:
- Scores that rank how suitable each hospital
- Logs that show how the system made its decisions
- Confidence levels that reveal how sure the system is about each recommendation
-These outputs are useful for debugging, upgrading the system, or even reporting to healthcare organizations.
- In Summary: What Makes the Output So Helpful?
The output of the hospital recommendation system is more than just a list—it's a smart, well-organized guide that considers what truly matters to each user. Whether you're looking for cost-effective care, high-quality specialists, or reliable patient experiences, the system brings together all the important details in one place.
By combining machine learning intelligence with real-world patient voices, it helps people make better healthcare decisions—quickly, confidently, and without confusion.

IX) Conclusion

Making healthcare decisions—especially choosing the right hospital—can be stressful and confusing, particularly during emergencies or serious health situations. That's where this project steps in. By using machine learning, we've created a system that helps simplify and improve the hospital selection process for patients. Instead of just focusing on basic things like how far the hospital is or what it costs, this system looks at the whole picture. It considers what other patients are saying in their reviews, the quality of medical services offered, the experience of doctors, the cost of treatment, and more. Thanks to Natural Language Processing (NLP), it can even understand the tone and meaning behind patient feedback—not just star ratings. The real strength of this system is how it combines data-driven intelligence with real human experiences. It doesn't just list hospitals—it recommends the ones that truly fit the patient's needs. This makes it easier for people to make confident, well-informed decisions, especially when time and clarity matter most .Beyond helping patients, this system can also be useful for doctors and healthcare staff. By automating parts of the referral and recommendation process, it helps save time and reduce pressure on healthcare professionals. Although the system already performs well, there's plenty of potential to expand. In the future, it could include real-time hospital updates, support more languages, connect with health records, and even work offline for use in rural areas
- In Summary : This project shows how technology—when used thoughtfully—can make healthcare more efficient, accessible, and personal. The hospital recommendation system is a meaningful step toward improving how people find care, making a usually stressful process a little more manageable and a lot more reliable.

X) References:

1) Singh and Kumar (2017) worked on a straightforward hospital referral system that ranked hospitals based on things like location and specialty, laying the groundwork for more personalized models.
2) Kumar and Sharma (2020) introduced machine learning techniques that used patient records and hospital features to improve hospital recommendations, showing better accuracy than earlier methods.
3) Patel and colleagues (2021) applied a K-Nearest Neighbours algorithm, focusing on matching hospitals with patients' symptoms and treatment

history, proving machine learning can really sharpen hospital suggestions.

4) Zhang et al. (2022) used deep learning for sentiment analysis, reading patient reviews to understand feelings behind ratings, which helped make recommendations reflect real patient experiences.

5) Ali, Khan, and Abbas (2023) created a hybrid system mixing collaborative filtering with sentiment analysis, improving how hospitals are suggested by combining different types of data.

6) Chen and Huang (2019) developed an intelligent system that uses both patient preferences and hospital details, making recommendations more personalized and practical.

7) Roy and Mukherjee (2020) reviewed various machine learning healthcare recommenders, giving a good overview of strengths and challenges in the field.

8) Wang and Li (2018) employed Support Vector Machines to classify patient data and suggest suitable hospitals, achieving good performance in hospital recommendation.

9) Lin and Xu (2019) focused on natural language processing to analyse patient feedback, unlocking insights from free-text reviews that traditional systems often miss.

10) Gupta and Verma (2021) examined collaborative filtering methods applied to hospital recommendations, highlighting benefits and difficulties when using these approaches.

11) Huang and Zhao (2022) surveyed deep learning methods used in healthcare recommendation systems, discussing how complex models can better understand patient needs.

12) Zhang and Zhao (2019) built a hospital recommendation model using random forest algorithms, showing that ensemble learning techniques can boost recommendation accuracy.

13) Chen and Tang (2020) designed a hybrid healthcare recommender combining patient preferences with hospital data, offering a balanced and effective recommendation.

14) Singh and Kumar (2021) created a sentiment-aware recommendation system that factors in emotional tones from patient reviews, improving user trust in suggestions.

15) Li and Wu (2018) applied KNN for hospital recommendations focused on patient-centred care, showing the importance of symptom similarity in matching.

16) Chen and Zhang (2019) proposed an intelligent healthcare provider recommender using ensemble learning to combine different prediction methods for better results.

17) Patel and Desai (2020) used hybrid machine learning techniques for hospital recommendations, mixing algorithms to handle complex healthcare data.