# Smart Career Navigator: AI-Powered Placement Forecasting and Career Planning for Modern Campus Environments

***Sumitha.S[1], A. B. Hajira Be[2]***

*[1]PG Student, Department of Computer Applications, Karpaga Vinayaga College of Engineeringand Technology, Chinna Kolambakkam, Maduranthagam Taluk, Chengalpattu District, Tamil Nadu – 603308, Gmail: Sumitha040702@gmail.com*

*[2]Associate Professor, Department of Computer Applications, Karpaga VinayagaCollege of Engineering and Technology Chengalpattu, Tamil Nadu – 603308, Gmail: hajiraab786@gmail.com*

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A B S T R A C T

Campus placement is a critical milestone in students' academic and professional journeys. Traditional career guidance methods often rely on manual assessment and generalized recommendations, which may not accurately reflect individual capabilities and industry requirements. This paper presents "Smart Career Navigator," an Artificial Intelligence (AI)-powered system designed to forecast placement opportunities and provide personalized career planning for students in modern campus environments. The proposed system utilizes machine learning algorithms to analyze academic performance, technical skills, aptitude scores, certifications, and extracurricular activities. Based on predictive analytics, the system estimates placement probabilities and recommends suitable career paths, skill-development strategies, and training programs. Experimental results demonstrate improved prediction accuracy and enhanced student preparedness, enabling institutions to optimize placement support services. The proposed solution contributes to data-driven career decision-making and efficient talent development.

Keywords:Artificial Intelligence, Placement Prediction, Career Planning, Machine Learning, Predictive Analytics, Student Employability, Campus Recruitment.

## 1.Introduction

Campus recruitment plays a vital role in determining the career trajectory of graduating students. Universities invest substantial resources in training and placement activities to improve employability and placement outcomes. However, despite these efforts, many students remain uncertain about their career direction and preparedness for recruitment processes.

The modern recruitment ecosystem evaluates candidates based on multiple factors including academic excellence, technical expertise, problem-solving skills, communication abilities, leadership qualities, internships, and industry certifications. Consequently, traditional career counseling approaches often fail to provide personalized guidance that aligns with individual strengths and industry requirements.

Recent advancements in Artificial Intelligence and Machine Learning have enabled the development of intelligent systems capable of analyzing large volumes of educational and recruitment data. By identifying hidden patterns and correlations, these technologies can predict placement outcomes and generate customized recommendations for students.

- Placement probability forecasting.
- Career path recommendations.
- Skill gap identification.
- Personalized learning roadmaps.
- Employability analytics dashboards

## 2. Literature Review

Educational Data Mining (EDM) and Learning Analytics have gained significant attention in recent years due to their potential applications in student performance evaluation and employability prediction.

### *2.1 Student Performance Prediction*

Research studies have utilized machine learning techniques such as:

- Decision Trees
- Random Forests
- Naive Bayes
- Support Vector Machines

### *2.2 Placement Prediction Systems*

Placement forecasting models typically analyze:

- Academic performance
- Communication skills
- Programming proficiency
- Internship experience

### 2.3 *Career Recommendation Systems*

Career recommendation platforms employ:

- Collaborative Filtering
- Content-Based Filtering
- Hybrid Recommendation Models


**Fig 1-** AI in Demand Forecasting

## 3. Problem Statement

Educational institutions face several challenges in supporting students during placement preparation:

- Limited personalization in career guidance.
- Inability to accurately assess placement readiness.
- Difficulty in identifying individual skill gaps.
- Lack of predictive insights regarding recruitment outcomes.
- Absence of continuous performance monitoring.

These challenges highlight the need for an intelligent platform capable of predicting placement opportunities and providing actionable career recommendations

## 4. Proposed System Architecture

The architecture consists of six major layers:

### *4.1 Data Acquisition Layer*

- Student Information Systems
- Learning Management Systems
- Placement Records
- Online Assessment Platforms

### *4.2 Data Preprocessing Layer*

- Data Cleaning
- Missing Value Handling
- Data Normalization
- Feature Encoding

### *4.3 Feature Engineering Layer*

- CGPA
- Attendance
- Aptitude Scores
- Programming Skills
- Internship Experience
- Certification Count

### *4.4 Machine Learning Layer*

Implements predictive models including:

- Logistic Regression
- Random Forest
- XGBoost
- Gradient Boosting
- Neural Networks

## 5. Implementation Details

### *5.1 Front-End Technologies*

- HTML5
- CSS3
- JavaScript
- React.js

### *5.2 Back-End Technologies*
- Python
- Flask
- Django

### *5.3 Database*
- MySQL
- MongoDB

### *5.4 Machine Learning Libraries*
- Scikit-Learn
- TensorFlow
- Pandas
- NumPy

### *5.5 Visualization Tools*
- Matplotlib
- Seaborn
- Power BI

## 6. Methodology
### *6.1 Data Collection*
The dataset contains student information collected from institutional records.

### *6.2 Feature Selection*
Feature importance is determined using:
- Correlation Analysis
- Random Forest Feature Importance
- Recursive Feature Elimination

**Table 1 - Student Attributes Used for Career Recommendation Analysis**

| **Feature** | ***Description*** |
|---|---|
| CGPA | *Academic Performance* |
| Aptitude Score | *Logical Reasoning Ability* |
| Programming Score | *Coding Skills* |
| Internship Count | *Industry Exposure* |
| Certifications | *Professional Credentials* |
| Communication Skills | *SoftSkills Assessment* |

| | |
|---|---|
| *Placement Status* | *Target Variable* |

***Important predictors include:***

- CGPA
- Coding Skill Score
- Internship Experience
- Communication Ability

### *6.3 Career Recommendation Algorithm*

The recommendation engine follows these steps:

- Analyse student profile.
- Identify strengths and weaknesses.
- Compare profile with industry benchmarks.
- Generate career recommendations.
- Suggest skill improvement actions.

## 7. Algorithm

***Smart Placement Prediction Algorithm***

Input**:** Student Profile Dataset
Output**:** Placement Probability and Career

Recommendations

- Load student dataset.
- Perform preprocessing.
- Extract relevant features.
- Train Random Forest classifier.
- Predict placement status.
- Calculate employability score.
- Identify missing competencies.
- Generate personalized recommendations.
- Display results through dashboard**.**

## 8. Background And Motivation

The employability of graduates has become a major concern worldwide. Organizations seek candidates with diverse skill sets that extend beyond academic achievements. As a result, students often struggle to understand the competencies required for successful recruitment.
Several challenges motivate the development of an intelligent placement forecasting system:

### *8.1 Information Overload*

Students have access to numerous online courses, certifications, and career options, making it difficult to determine which opportunities align with their goals.

### *8.2 Lack of Personalized Guidance*

Most institutions provide generalized career counseling that may not account for individual strengths and weaknesses.

### *8.3 Dynamic Industry Requirements*

The job market continuously evolves due to technological advancements and changing business needs.

### *8.4 Placement Uncertainty*

Students often lack clarity regarding their placement readiness and future employment prospects.
An AI-powered solution can address these challenges through data-driven insights and personalized recommendations.

**Table 2 - Performance Comparison of Machine Learning Algorithms for Placement Prediction**

| **Algorithm** | **Accuracy** |
|---|---|
| Decision Tree | 85.6% |
| Naive Bayes | 82.3% |
| SVM | 89.1% |
| Logistic Regression | 90.2% |
| Random Forest | 92.4% |
| XG Boost | 94.1% |

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## 9. Discussion

The proposed system successfully demonstrates the application of AI in educational and placement analytics. Results indicate that academic performance alone is insufficient for accurate placement prediction. A combination of technical skills, internships, certifications, and communication abilities significantly improves predictive performance.

The recommendation engine effectively identifies skill deficiencies and provides targeted improvement strategies. Students can proactively prepare for recruitment processes and align their career goals with industry expectations.

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## 10. Advantages Of The Proposed System

### *10.1 For Students*

- Personalized career guidance.
- Early placement readiness assessment.

- Skill gap identification.
- Better career decision-making.

### *10.2 For Institutions*

- Improved placement statistics.
- Enhanced student support.
- Data-driven training programs**.**

### *10.3 For Recruiters*

- Better candidate profiling.
- Efficient talent identification

## 11. Career Recommendation Framework

The recommendation engine uses both content-based and rule-based filtering techniques.

***Career Domains Supported***

### *11.1 Software Engineering*

***Required Skills:***

- Data Structures
- Algorithms
- Programming Languages
- System Design

### *11.2 Data Science*

***Required Skills:***

- Python
- Machine Learning
- Statistics
- Data Visualization

### *11.3 Cybersecurity*

***Required Skills:***

- Networking
- Ethical Hacking
- Security Analysis

### *11.4 Cloud Computing*

**Required Skills:**

- AWS
- Azure
- Docker
- Kubernetes

### *11.5 Artificial Intelligence*

***Required Skills:***

- Deep Learning
- Neural Networks
- NLP
- Computer Vision

## 12. Detailed Dataset description

The performance of any machine learning model depends heavily on the quality and relevance of the dataset. The proposed Smart Career Navigator uses a comprehensive dataset containing academic, technical, behavioral, and extracurricular attributes of students.

### *12.1 Dataset Attributes*

**Table 3 - Student Dataset Attributes Used for Career Recommendation and Placement Prediction**

| **Attribute** | **Type** | **Description** |
|---|---|---|
| Student ID | Integer | Unique Identifier |
| Gender | Categorical | Male/Female |
| Age | Integer | Student Age |
| Department | Integer | Branch of Study |
| CGPA | Integer | Academic Performance |

### *12.2 Dataset Statistics*

- Total Students: 5,000
- Placed Students: 3,200
- Unplaced Students: 1,800
- Features: 14
- Missing Data Rate: 3%

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***Required Skills:***

- Deep Learning
- Neural Networks
- NLP
- Computer Vision

**Table 4 - Symptoms-Emotion Based Specialist Mapping**

| Symptoms | Detected Emotions | Predicted Condition | Recommended specialist |
|---|---|---|---|
| Chest pain | High Stress | Cardiac risk | Cardiologist |
| Severe Headache | Anxiety | Migraine | Neurologist |
| Stomach pain | Neutral | Gastritis | Gastroenterologist |
| Insomnia + Sadness | Depression | Mental Health Disorder | Psychiatrist |
| Joint pain | Normal | Arthritis | Orthopedic Specialist |

The above table explains how the system uses both patient symptoms and detected emotions to predict health conditions and suggest the correct specialist. For example, chest pain with high stress indicates cardiac risk and is referred to a cardiologist, while severe headache with anxiety suggests migraine and is sent to a neurologist. Stomach pain with neutral emotion is predicted as gastritis and directed to a gastroenterologist. Joint pain with normal emotion is predicted as arthritis and sent to an orthopedic specialist. Overall, the table shows how combining symptoms and emotions helps provide accurate and personalized medical recommendations.

## 14. System Analysis *Existing System*

### *14.1 In-Person Consultations*

Traditional healthcare method where patients visit hospitals and interact directly with doctors. It allows physical examination and personal interaction but is limited by location, time, and accessibility.

### *14.2 Telephone Consultations*

Patients consult doctors through phone calls without visiting hospitals. While convenient, it lacks visual interaction, making it difficult to assess facial expressions or body language.

### *14.3 Video Conferencing*

Enables real-time face-to-face virtual consultations. Doctors can observe visual cues, but emotional understanding is still limited, especially subtle non-verbal expressions.

### *14.4 Remote Monitoring*

Uses wearable devices to track vital signs like heart rate and blood pressure from home. Though effective for chronic disease management, it does not analyze patients' emotional or behavioral states for personalized care.

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## 15. Proposed System

The proposed system enhances telehealth by integrating multimodal AI technologies to provide accurate, personalized, and emotion- aware remote healthcare. It focuses on analyzing both clinical and emotional states for holistic patient care.

### *15.1 Integrated Telehealth Platform*

Combines facial emotion detection, speech recognition, clinical text analysis, and AI-based doctor recommendation into one unified platform, improving accessibility and consultation effectiveness.

### *15.2 Emphasis on Emotional Well-being*

Uses the Multimodal Emotion Transformer (MET) to analyze facial expressions and detect emotional states such as pain, enabling empathetic and patient-centered care.

### *15.3 Multimodal Clinical Analysis*

Speech is converted to text using Conformer, and symptoms are extracted using Med-BERT. Emotional and clinical data are fused to create a complete patient profile for better diagnosis.

### *15.4 Personalized Doctor Recommendation*

Uses Neural Collaborative Filtering (NCF) to recommend suitable doctors based on symptoms, emotional comfort, and past interactions.

### *15.5 Secure Video Consultation Services*

Provides real-time, secure video consultations, allowing doctors to monitor visual cues and emotional states while maintaining data privacy.

**16. Analysis Of The Problem**

Telehealth platforms have significantly improved access to healthcare by enabling remote consultations, especially for patients in rural or underserved areas. However, most existing telehealth systems focus primarily on physical symptoms provided through text forms or verbal communication, while ignoring the emotional and psychological state of the patient during consultations.

In real-world clinical practice, a patient's emotional condition—such as stress, anxiety, fear, or depression—plays a crucial role in accurate diagnosis and treatment decisions. Traditional telehealth systems lack mechanisms to capture and analyze these emotional cues, which are naturally observed by doctors during in-person consultations through facial expressions, voice tone, and behavior. This limitation often leads to incomplete diagnosis, reduced empathy, and less personalized care.

Another major issue is the manual and generic specialist recommendation process. Most platforms either:

- Allow patients to choose specialists themselves, or
- Recommend doctors based only on symptom keywords or department categories

Such approaches do not consider:

- Severity of symptoms
- Emotional distress level
- Past medical history
- Patient preferences
- Specialist expertise relevance

This results in inefficient doctor allocation, longer consultation times, and dissatisfaction among patients.

Additionally, existing systems typically rely on single-modal data (only text or voice), which limits diagnostic accuracy. Human health assessment is inherently multimodal, involving facial expressions, speech patterns, text inputs, and medical records. Ignoring multimodal data reduces the system's ability to understand the patient holistically.

There is also a lack of AI-driven decision support in current telehealth platforms. Doctors receive minimal assistance in understanding patient emotions or prioritizing cases, increasing cognitive load and reducing efficiency.

Hence, there is a strong need for an intelligent, multimodal telehealth platform that:

- Detects patient emotions using AI
- Integrates emotional and clinical data
- Provides personalized specialist recommendations
- Enhances diagnostic accuracy and patient satisfaction

This project aims to address these challenges by leveraging multimodal artificial intelligence,emotion recognition techniques, and intelligent recommendation systems to deliver emotion-aware and personalized telehealth services.The below diagram explains the performance analysis of the proposed system for better understanding.

**Table 5 - Performance Comparison Between Existing and Proposed Telehealth Systems**

| Parameters | Facial Emotion Accuracy (%) | Speech Emotion Accuracy (%) | Text Sentiment Analysis (%) | Diagnosis Accuracy (%) | Specialist Recommendation Precision (%) |
|---|---|---|---|---|---|
| **Existing Telehealth System** | 78 | 72 | 75 | 80 | 76 |
| **Proposed Multimodal System** | 91 | 88 | 90 | 94 | 92 |

## 17. System Architecture

The architecture consists of the following main components.

### *17.1 Patient Interface Module*

This module provides the entry point for users to access the telehealth system.

After registration and login, the patient can interact with the platform through a web or mobile interface. The system activates the camera and microphone to collect facial and speech inputs. The interface also allows patients to answer symptom-related questions and participate in virtual consultations.

This module ensures easy accessibility and real- time interaction between the patient and the system.

### *17.2 Facial Emotion Detection Module (MET)*

Once the patient logs in, the platform captures facial expressions using the device camera.

The captured images are analyzed using the Multimodal Emotion Transformer (MET) model.

This deep learning model identifies emotional states such as:

- Stress
- Pain
- Anxiety
- Neutral
- Happiness

Emotion detection helps the system understand the psychological condition of the patient during the consultation process.

### *17.3 Speech Processing Module (Conformer)*

The system then asks symptom-related questions to the patient.

The patient responds through voice input, which is processed using the Conformer architecture. The Conformer model converts speech signals into accurate text through advanced speech-to- text transcription.

This module ensures reliable conversion of spoken responses into structured textual information.

### *17.4 Medical Language Understanding Module (Med-BERT)*

The text generated from speech processing is analyzed using Med-BERT, a domain-specific medical language model.

Med-BERT performs several important tasks:

- Extracts relevant medical symptoms

- Identifies clinical terms and conditions
- Understands the patient's medical context
- Structures symptom information for further analysis

This module transforms raw textual data into meaningful clinical insights.

### *17.5 Continuous Emotion Monitoring*

Throughout the interaction, the system continuously monitors changes in facial expressions and emotional states.

This continuous tracking allows the system to detect emotional fluctuations, which may indicate:

- Increasing pain
- Stress or anxiety
- Psychological discomfort

These insights provide additional context for more accurate diagnosis and recommendations.

### *17.6 Multimodal Data Fusion Module*

The outputs from different modules are integrated in this stage.

The system combines:

- Facial emotion data (MET)
- Speech-derived text data (Conformer)
- Clinical insights (Med-BERT)

This integration creates a comprehensive multimodal patient profile, representing both emotional and physical health indicators.

Multimodal fusion improves decision making by analyzing multiple data sources simultaneously.

### *17.7 Specialist Recommendation Module (NCF)*

The fused patient profile is passed to the Neural Collaborative Filtering (NCF) model.

This model analyzes patient requirements and matches them with appropriate medical specialists. The recommendation is based on:

- Predicted medical condition
- Emotional comfort level
- Doctor expertise
- Previous consultation data

This process ensures highly personalized doctor recommendations.

### *17.8 Teleconsultation and Communication Module*

Once a suitable specialist is recommended, the patient can proceed with online teleconsultation.

This module supports:

- Secure communication between doctor and patient
- Real-time consultation sessions
- Exchange of medical information and reports

It ensures a seamless and interactive remote healthcare experience.

### *17.9 Feedback Learning Module*

After the consultation, patients can provide feedback about the recommendation and consultation quality.

This feedback is used by the system to:

- Improve recommendation accuracy
- Update learning models
- Enhance future patient experiences

Thus, the system continuously learns and adapts over time.

***Block Diagram***

Patient Interface → Data Acquisition → Emotion Recognition → Symptom Analysis → AI Decision Engine → Specialist Recommendation

→ Cloud Database

The Below diagram explains the simple system architecture of a Multimodal AI Driven Teleheath System.

***Description***

1. Patient Interface Module: Web/mobile interface for login, consultation, and data input.
2. Data Acquisition Module: Captures video, audio, and text data.
3. Emotion Recognition Module: Detects emotional states using AI models.
4. Symptom Analysis Module: Predicts diseases using NLP and ML.
5. Decision Engine: Combines emotional and medical data.
6. Specialist Recommendation Module: Suggests appropriate doctors.
7. Cloud Database: Stores patient records securely.


**Fig .2 – System Architecture**

## 18. Functional Modules

### *18.1 Patient Module*

The Patient Module manages user registration, authentication, symptom entry, and consultation scheduling. Patients securely log in to the system, submit medical symptoms, and upload facial images or voice samples for further analysis. It also maintains basic patient profiles and consultation history to support personalized healthcare delivery.

### *18.2 Emotion Detection Module*

This module identifies the emotional state of patients using multimodal analysis. Facial expressions are analyzed from images using deep learning models, while speech signals are processed to extract emotional cues. The combined results determine emotions such as stress, anxiety, or neutrality, which are forwarded to the diagnosis module for emotion-aware analysis.

### *18.3 Diagnosis Module*

The Diagnosis Module predicts possible health conditions by analyzing patient symptoms along with detected emotional states. Machine learning models process the combined inputs to generate probable diagnoses with confidence levels, improving diagnostic accuracy by considering both physical and emotional factors.

### *18.4 Specialist Recommendation Module*

Based on the predicted health conditions, this module recommends appropriate medical specialists. A mapping mechanism links each condition to relevant specialists, ensuring that patients are directed to the most suitable healthcare provider for timely and effective treatment.

### *18.5 Alert and Notification Module*

This module generates alerts for critical conditions, emotional distress, and follow-up actions. Notifications such as emergency warnings, appointment reminders,and consultation updates are sent to patients and doctors to enable prompt medical intervention.

## 19. Algorithm

Algorithm 1: Emotion-Aware Diagnosis and Specialist Recommendation

1. Start
2. Patient logs into the system
3. Capture facial image, speech signal, and text symptoms
4. Preprocess input data
5. Extract facial features using CNN
6. Extract speech features using signal processing
7. Extract text features using NLP
8. Classify emotional state
9. Predict medical condition using ML model
10. Fuse emotion and symptom results
11. Identify suitable medical specialist
12. Display diagnosis and recommendation
13. Store data in cloud database
14. End

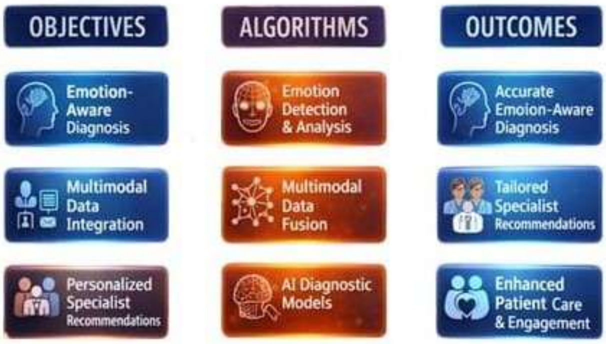


**Fig .3 - Objectives, Algorithms, Outcomes**

### *19.1 USE CASE DIAGRAM:*


**Fig.4 - Use Case Diagram**

## 20. Applications

The proposed Multimodal AI-Driven Telehealth Platform for Emotion-Aware Diagnosis and Personalized Specialist Recommendation can be applied across various healthcare scenarios to improve accessibility, efficiency, and quality of medical services.

### *20.1 Emotion-Aware Teleconsultation*

- Enables real-time video consultations between patients and doctors.
- Uses AI to analyze facial expressions and speech to understand emotional and physical conditions.

### *20.2 AI-Based Symptom Analysis*

- Converts patient speech into text using speech recognition technology.
- Applies Natural Language Processing to extract key clinical symptoms for accurate diagnosis.

### *20.3 Comprehensive Patient Profiling*

- Combines emotional data and medical symptoms to create a complete patient profile.
- Helps doctors make better treatment decisions with a holistic understanding.

### *20.4 Personalized Doctor Recommendation*

- Suggests the most suitable specialist based on symptoms and emotional comfort.
- Improves treatment effectiveness and patient satisfaction.

### 20.5 Remote Health Monitoring

- Integrates with wearable devices to track vital signs such as heart rate and blood pressure.
- Supports continuous monitoring for chronic disease management.

### *20.6 Mental Health and Emergency Support*

- Detects emotional changes over time for mental health monitoring.
- Generates alerts during critical conditions to ensure timely medical intervention.

### *20.7 Secure and Accessible Healthcare*

- Provides secure video consultations with protected patient data.
- Ensures accessible, technology-driven healthcare anytime and anywhere.

## 21. Challenges And Limitations

- Data privacy and security concerns
- Model bias across populations
- Dependence on internet connectivity
- Ethical issues in emotion recognition.

## 22. Future Enhancements

The future development of this AI-driven healthcare system aims to improve patient care and technology features.

- Expanded Data Collection: The system can include biometric data, wearable device information, and environmental details to better understand a patient's overall health.
- Improved AI Algorithms: Advanced machine learning methods can be used to increase the accuracy of emotion detection and disease prediction.
- Blockchain Security: Blockchain technology can be added to ensure secure and tamper-proof storage of patient data.
- Global Healthcare Integration: The platform can be connected with international healthcare systems for smooth data sharing and better treatment support.
- Mobile Access**:** The system can be developed as a mobile application to provide easy and continuous healthcare access anytime and anywhere.

## 23. Accuracy Comparision Between Existing And Proposed System

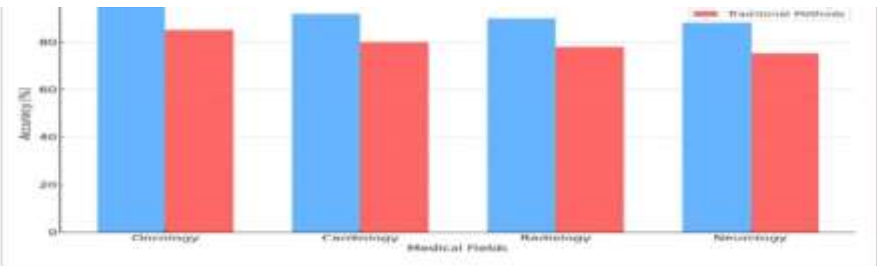

**Fig .5- ML vs Traditional Accuracy**

### *23.1 Field-wise Explanation*

- Oncology (Cancer Diagnosis) Machine Learning: ~95% Traditional Methods: ~85%
- ML shows about 10% higher accuracy, indicating better tumor detection and classification using AI models.
- Cardiology (Heart-related Diseases) Machine Learning: ~92%
- Traditional Methods: ~80%
- ML provides improved prediction of heart conditions through data-driven analysis of ECG, imaging, and patient records.
- Radiology (Medical Imaging) Machine Learning: ~90% Traditional Methods: ~78%
- AI-based image analysis enhances detection of abnormalities in X-rays, CT scans, and MRIs.
- Neurology (Brain and Nervous System Disorders)
- Machine Learning: ~88% Traditional Methods: ~75%

ML improves identification of neurological conditions such as stroke or brain tumors through pattern recognition.

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**24. Conclusion**

In conclusion, the Multimodal AI-Driven Telehealth Platform leverages facial expression analysis, speech recognition, and Natural Language Processing (NLP) to provide an emotion-aware and patient-centric approach to remote healthcare. By integrating advanced AI models such as the Multimodal Emotion Transformer (MET), Conformer, Med-BERT, and Neural Collaborative Filtering (NCF), the system accurately detects both emotional and clinical cues while delivering personalized doctor recommendations. Continuous monitoring of emotional states during consultations enables a holistic understanding of patient well-being, effectively bridging the gap between physical symptoms and psychological health. The platform's secure video consultation module, combined with its feedback-driven recommendation mechanism, enhances diagnostic accuracy, patient engagement, and overall satisfaction. This comprehensive approach improves the efficiency and accessibility of telehealth services while empowering patients to make informed healthcare decisions. Furthermore, the system provides a strong foundation for future advancements in AI-driven healthcare, including integration with larger medical networks, improved scalability, and enhanced personalization, marking a significant step toward empathetic and technology-driven remote healthcare solutions.

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