



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** III **Month of publication:** March 2026

DOI: <https://doi.org/10.22214/ijraset.2026.78377>

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A Smart Patient Monitoring System for Home Healthcare

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Abstract: For patients getting care at home, home health-care necessitates ongoing observation and prompt medical assistance. In order to facilitate efficient coordination between home nurses, physicians, administrators, and ambulance services, this study suggests an AI-driven home healthcare monitoring system. While doctors document clinical observations and treatment information, home nurses routinely update patients' vital signs and health condition. To find unusual medical conditions, the gathered data is evaluated. The system creates alerts in an emergency to prompt medical professionals, nurses, and ambulance personnel to act quickly. The suggested approach facilitates effective home-based healthcare monitoring, improves care coordination, and increases patient safety.

I. INTRODUCTION

The growing number of elderly patients and people with chronic illnesses has led to a huge increase in demand for home healthcare services. Home-based care lessens hospital overcrowding while enabling patients to get medical care in a comfortable setting. However, manual monitoring and delayed communication are common features of traditional home healthcare systems, which might hinder prompt medical intervention in emergency situations. The creation of intelligent healthcare systems that facilitate ongoing patient monitoring and effective professional coordination has been made possible by developments in digital health technologies. When it comes to monitoring patient conditions, taking vital signs, and delivering primary care, home nurses are essential. The accuracy of patient assessment and treatment planning can be increased by combining their observations with clinical advice from physicians. Demographic shifts, technology breakthroughs, and the growing need for patient-centered treatment are all driving a major revolution in the global healthcare industry. The increasing focus on home healthcare services, which seek to give patients ongoing medical care in their own homes, is one of the most significant changes. Elderly people, those with chronic illnesses, post-operative patients, and those in need of long-term monitoring all benefit greatly from this strategy. In addition to enhancing patient comfort and quality of life, home-based care eases the strain on medical facilities and infrastructure. Despite its benefits, traditional home healthcare has a number of drawbacks. Manual record-keeping and routine examinations by medical experts are frequently the mainstays of patient monitoring. This may lead to inadequate coordination during emergencies, delayed detection of health decline, and delayed communication amongst caregivers. These difficulties show how home healthcare monitoring needs to be more organized and technologically advanced in order to guarantee ongoing observation, prompt decision-making, and quick emergency intervention. New chances to improve home healthcare services have been made possible by developments in digital health technologies, such as electronic health records, remote monitoring systems, and intelligent data analysis techniques. Real-time patient health data collection, storage, and analysis are made possible by smart healthcare systems, enabling medical professionals to make well-informed judgments. These systems are especially helpful in home care situations, where patients may not always have access to urgent medical attention due to their physical distance from hospitals. In the home healthcare environment, home nurses are essential. They are in charge of visiting patients on a regular basis, keeping an eye on vital signs, giving prescriptions, and noting any changes in the patients' state of health. Home-based medical care is based on their observations. Nevertheless, clinical input from physicians or emergency services is not successfully integrated with nurse-recorded data in many current systems. Delays in responding, fragmented care, and a higher risk to patient safety might result from this lack of integration. Emergency management is a crucial issue in home healthcare. Individuals getting at-home care may develop unexpected health issues that need to be treated right away. Contacting doctors or scheduling ambulance services could take up crucial time in the absence of an effective alarm and communication system. Patient outcomes can be greatly impacted by delayed emergency care, especially when heart problems, respiratory distress, or neurological disorders are involved.

Thus, a dependable system for identifying abnormal situations and organizing emergency action is essential to a successful home healthcare system. By automating data analysis and assisting with clinical decision-making, intelligent healthcare systems have been investigated in recent years to address these issues. These tools can help medical workers discover possible problems early on by evaluating patient vitals and clinical notes. These systems can notify pertinent parties, such as physicians, nurses, and emergency responders, when paired with alert mechanisms, allowing for prompt intervention. However, a lot of current systems place little emphasis on nurse-assisted home care workflows and instead concentrate on hospital-based monitoring or wearable-device-centered strategies. In order to facilitate nurse-assisted patient care in home settings, this article suggests a smart home healthcare monitoring system. The suggested approach unifies several stakeholders into a single digital platform, including administrators, physicians, home nurses, and ambulance services. The administrator module is in charge of personnel assignments, patient registration, and system supervision. While doctors give clinical observations, diagnoses, and treatment plans, home nurses are in charge of updating patients' daily health status and vital signs. This integrated approach guarantees that a centralized system contains all pertinent patient data.

The suggested system uses sophisticated data analysis methods to handle patient data gathered from physicians and home nurses. The system looks for aberrant situations and possible health hazards by evaluating clinical inputs and health metrics. Automated warnings are created in emergency situations and sent to physicians, nurses, and ambulance services to guarantee prompt action. This system decreases delays during emergencies and lessens reliance on manual communication. The proposed system's emphasis on care coordination is one of its main advantages. Maintaining continuity of care requires effective communication between physicians and home nurses. The technology improves collaboration amongst healthcare providers by offering a common platform for data entry, monitoring, and alarms. Without the need for frequent hospital stays, doctors can evaluate patient conditions, check nurse-updated data remotely, and give prompt medical advice. This lowers needless hospital admissions and increases efficiency. The suggested approach not only enhances patient safety but also helps healthcare administrators by giving them information about nurse actions and patient monitoring status. Administrators can monitor the provision of care, guarantee responsibility, and maximize the use of available resources. Maintaining service quality and overseeing extensive home healthcare services require this kind of visibility. Scalable and flexible solutions that can be incorporated into current healthcare workflows are crucial, as seen by the growing use of smart healthcare systems. Because of its adaptability and extensibility, the suggested system can accommodate a variety of patient kinds and healthcare situations. The approach advances the more general objective of creating effective and sustainable healthcare infrastructures by utilizing digital platforms for communication and monitoring. New opportunities to solve these issues have been made possible by recent developments in healthcare information technology. Electronic health records, cognitive data processing methods, and digital healthcare platforms have all shown promise in improving clinical support and patient monitoring. Centralized data storage, real-time patient information access, and automated analysis to support medical personnel are all made possible by smart healthcare systems. In home healthcare settings, where prompt intervention is more challenging due to physical distance from hospitals, these technologies are very helpful. In the home healthcare environment, home nurses are essential. Regular patient visits, medicine administration, vital sign monitoring, and the observation of behavioral and physical changes are all part of their duties. They serve as a liaison between patients and physicians, which goes beyond providing basic treatment. However, the absence of integrated digital technologies that enable smooth contact with physicians and emergency services frequently limits the efficacy of home nurses. Because nurse observations are often documented in isolation, it is challenging to use this information to make well-informed clinical decisions. Emergency response management is a crucial issue in home healthcare. Sudden medical emergencies, such as cardiac arrhythmias, respiratory distress, or neurological problems, may occur in patients getting treatment at home. Nurses or caregivers may have to rely on manual phone calls or delayed reporting to get in touch with physicians or ambulance services in the absence of an organized alert system. The necessity for automated and coordinated emergency handling systems is highlighted by the fact that these delays might have a substantial influence on patient survival and recovery. Early detection of aberrant health patterns based on patient vital signs and clinical observations is made possible by the incorporation of intelligent analysis into home healthcare systems. In conclusion, the increasing need for home healthcare and the shortcomings of conventional monitoring techniques call for the creation of clever and comprehensive solutions. The smart home healthcare monitoring system described in this work prioritizes coordinated clinical decision-making, effective emergency response, and nurse-assisted care. The suggested method seeks to improve the efficacy, dependability, and quality of home-based healthcare services by tackling major issues such as fragmented communication, delayed action, and a lack of real-time monitoring.

II. RELATED WORKS

A. *Adaptation of autoencoder for sparsity reduction from clinical notes representation learning*

In order to improve learning from unstructured medical text, Le et al. proposed an autoencoder-based method to decrease sparsity in clinical note representations. The approach improves feature representation for healthcare analytics, but it does not offer real-time symptom analysis, severity estimate, or interactive patient-centered monitoring; instead, it primarily concentrates on retrospective clinical data.

B. *Evaluating a nurse-led narrative interview intervention with cancer patients with a first diagnosis*

In order to assist cancer patients at their initial diagnosis, Artioli et al. suggested a nurse-led narrative interview intervention that uses structured narratives to record patient experiences. The strategy places a strong emphasis on patient-centered communication and holistic care, showing viability and acceptability in clinical settings. Nevertheless, it is constrained by a small sample size and mostly qualitative results, and it lacks automated analysis, real-time risk assessment, and AI-driven severity prediction for scalable healthcare monitoring.

C. *Influence of standardized patient combined with narrative nursing teaching on experimental teaching of surgical nursing*

In order to enhance surgical nursing education outcomes, Tang and Gao investigated the incorporation of standardized patients with narrative nursing instruction. The method improves student involvement, communication abilities, and the efficacy of experiential learning; nevertheless, it is restricted to educational environments and ignores automated evaluation, data-driven customisation in patient care systems, and real-world clinical implementation.

D. *Changing the narrative for exercise-based prehabilitation: Evidence-informed and shared decision making when discussing the need for a total knee arthroplasty with patients*

In exercise-based prehabilitation talks for patients thinking about total knee replacement, Bandholm et al. highlighted narrative-based, collaborative decision-making techniques. Although the study emphasizes clinician-patient communication above computational modeling and lacks tools for real-time monitoring, symptom quantification, or AI-assisted decision support, it does enhance patient empowerment and evidence-informed communication.

E. *Effectiveness of narrative nursing on depression patients with suicide attempt*

In a preliminary randomized controlled trial, Junyu et al. assessed how well narrative nursing reduced depression in patients who had attempted suicide. The results show improvements in psychological outcomes and emotional expression, but the strategy lacks scalable automation, predictive analytics, and ongoing mental health severity assessment and mostly depends on human-led interventions.

F. *HSGA: A Hybrid LSTM-CNN Self-Guided Attention to Predict the Future Diagnosis From Discharge Narratives*

In order to forecast future diagnoses from discharge narratives, Harerimana et al. created HSGA, a hybrid LSTM-CNN model with self-guided attention. Although the approach enhances predictive performance on unstructured clinical text, it does not support real-time symptom tracking, interactive patient engagement, or early-stage risk severity estimation. Instead, it works with retrospective discharge data.

G. *The clinical efficacy of intravascular laser irradiation of blood (ILIB): A narrative review of randomized controlled trials*

Based on randomized controlled studies, D'iaz et al. provided a narrative review evaluating the clinical effectiveness of intravascular laser irradiation of blood (ILIB). Although the review is descriptive in style and lacks AI-based analysis, tailored treatment prediction, and dynamic clinical decision support, it does compile current data and therapeutic outcomes.

III. METHODOLOGY

A. *Data Gathering and Preparation*

Electronic health records (EHRs) are used to gather clinical data, such as patient information, clinical notes, vital signs, and test results. Textual data is cleaned by tokenizing phrases, eliminating noise, and standardizing medical language while keeping only stopwords that are clinically important.

B. Clinical Narrative Classification

From unstructured clinical notes, symptom-related information is extracted using a supervised text classification model. Relevant clinical factors, such as dysphagia, heart symptoms, and general health concerns, are used to classify extracted narratives. Meaningful text is filtered for additional analysis in this step.

C. LLM-Based Feature Extraction

The detected symptom narratives are processed by a large language model (LLM) in order to derive high-level clinical insights. The presence of symptoms, their severity levels (mild, moderate, and severe), and their temporal patterns (acute or chronic) are all identified by the LLM. Structured numerical and categorical features are created from extracted outputs.

D. Integration of Structured and Unstructured Data

Heart rate, blood pressure, oxygen saturation, test results, and other normalized structured data are combined with LLM-derived characteristics. The patient’s health status is comprehensively represented by this multi-modal feature set.

E. Risk Prediction and Evaluation

Dysphagia and cardiac risk are predicted using machine learning models such as Random Forest, Gradient Boosting, and XGBoost. Accuracy and F1-score are used to assess model performance in order to guarantee accurate clinical risk prediction.

IV. RESULTS AND DISCUSSIONS

A web-based AI healthcare platform for managing clinical narratives, physicians, home nurses, and ambulance services is successfully implemented using the suggested system. Dedicated role-based dashboards efficiently store, process, and display clinical data entered by physicians and nurses. For risk assessment, the system reliably extracts symptom-related data from clinical notes and combines it with patient vital signs. Administrative modules facilitate effective administration of ambulance availability, home nurse assignments, and doctor lists.

Real-time viewing of staff information and patient-related records is supported by the responsive user interface.

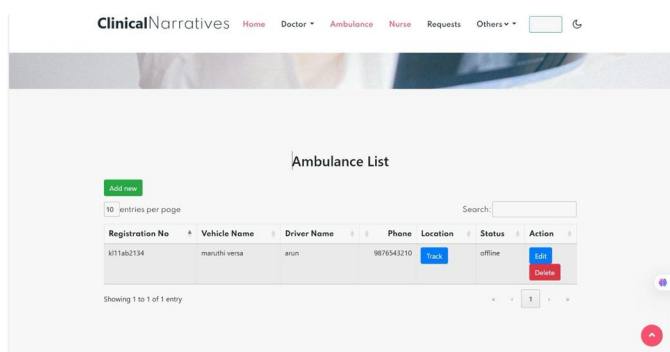


Fig. 1.

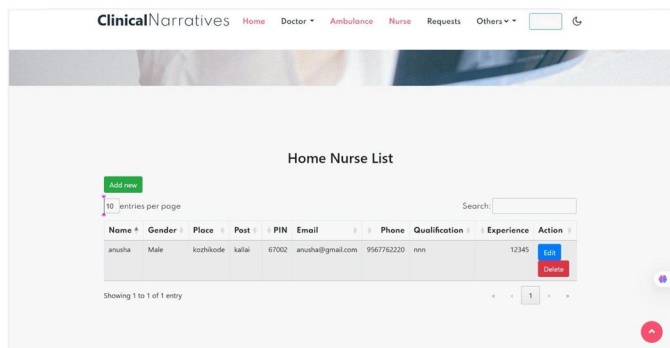


Fig. 2.

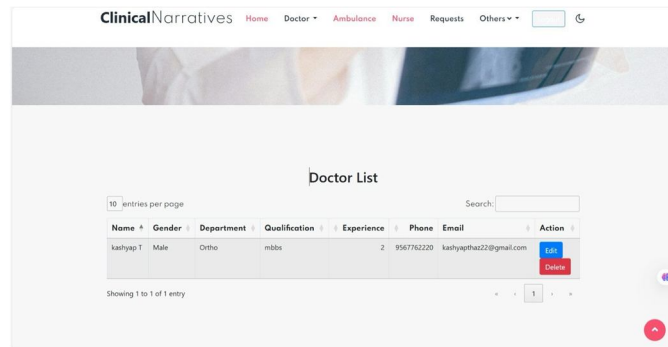


Fig. 3.

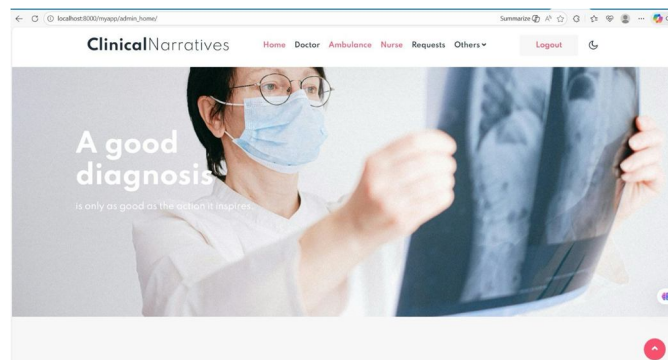


Fig. 4.

V. SYSTEM ARCHITECTURE

A. Image-Based Processing Flow

The patient's surroundings are captured by the camera in real time. Image preprocessing, including scaling, noise reduction, and normalizing, is applied to captured frames. An AI model that has been trained is given the preprocessed image to make predictions. A notice is produced based on the projected outcome. The user (doctor, nurse, or caregiver) receives the alert from the cloud server.

B. Training Flow for AI Models

For training, a dataset is gathered and preprocessed. The AI model is trained using the processed data. The model is retained and utilized again for real-time prediction after training. The image-based pipeline's prediction stage is directly supported by the saved model.

C. Text-Based Clinical Analysis

Clinical notes and patient descriptions are gathered into a text dataset. Text preprocessing (cleaning, tokenization, and normalization) is carried out. Word2Vec is used to transform the text into a numerical format. These features are used to train an NLP + ML model. For upcoming forecasts, the trained model is saved.

D. Patient Information Processing

The user enters clinical notes and symptoms related to the patient. Text processing is applied to the input text. The trained NLP + ML model receives the processed text. The patient's condition is predicted by the model. The user is shown the anticipated state of the patient.

E. Final Outcome

The technology integrates text-based clinical analysis with predictions based on images. The cloud platform provides users with condition information and timely notifications. In healthcare situations, this enhances early diagnosis, monitoring, and action.

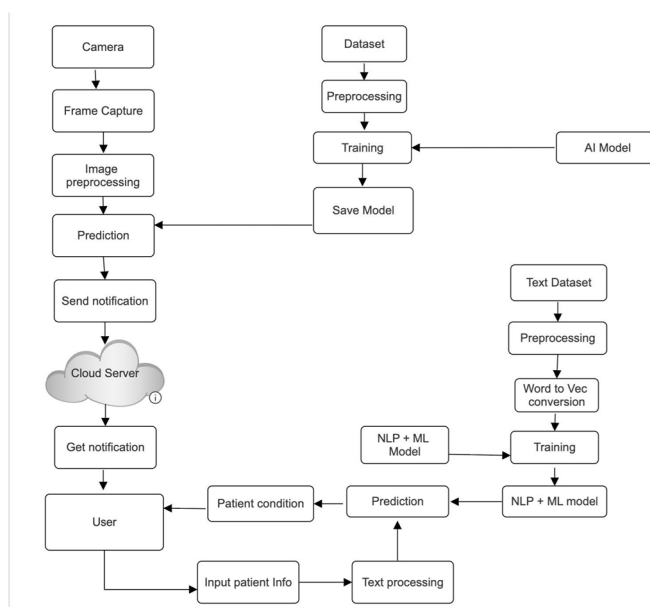


Fig. 5

VI. CONCLUSION

In order to facilitate early clinical risk prediction and better patient care in home healthcare settings, this project effectively presents an intelligent, AI-enabled healthcare monitoring system. The system efficiently processes both structured clinical data and unstructured medical narratives to produce significant health insights by combining machine learning, natural language processing, and large language model (LLM) approaches. By automating symptom extraction and condition assessment, the suggested method tackles a major issue in healthcare systems: accurate interpretation of complex clinical notes. The system uses LLM-based feature extraction and sophisticated text preprocessing to extract clinically relevant symptoms, severity levels, and temporal patterns from narrative data. A thorough multi-modal representation of the patient's health is produced by combining these extracted insights with structured patient data, such as vital signs and test results. When compared to conventional systems that only use structured data, this integration improves the precision and dependability of risk prediction. The role-based architecture of the suggested system, which consists of modules for administrators, physicians, home nurses, and ambulance services, is one of its main advantages. This architecture guarantees efficient coordination among healthcare stakeholders, safe access control, and well-organized data administration. Administrators may oversee staff assignments and system operations, doctors can record clinical notes and treatment data, and nurses can update patient vitals and progress. This kind of coordinated contact facilitates prompt therapeutic interventions and increases workflow efficiency. The system's prediction models, which include ensemble and tree-based classifiers, show consistent accuracy in recognizing heart-related risks and dysphagia. The system's potential to assist decision-making in actual healthcare situations is demonstrated by the evaluation findings, which show satisfactory accuracy and F1-score. Furthermore, the incorporation of real-time warning and notification methods facilitates prompt reaction to critical patient circumstances, hence mitigating any delays in the provision of care. All things considered, the suggested approach shows great promise for raising the standard of healthcare services by facilitating the early identification of health hazards, enhancing provider coordination, and assisting with data-driven clinical decisions. Future improvements, including adding more illness prediction models, sophisticated deep learning methods, and wearable device data, have a solid foundation thanks to the modular and scalable design. In conclusion, our study presents a practical and intelligent approach toward enhancing patient safety, efficiency, and outcomes in current healthcare systems.

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