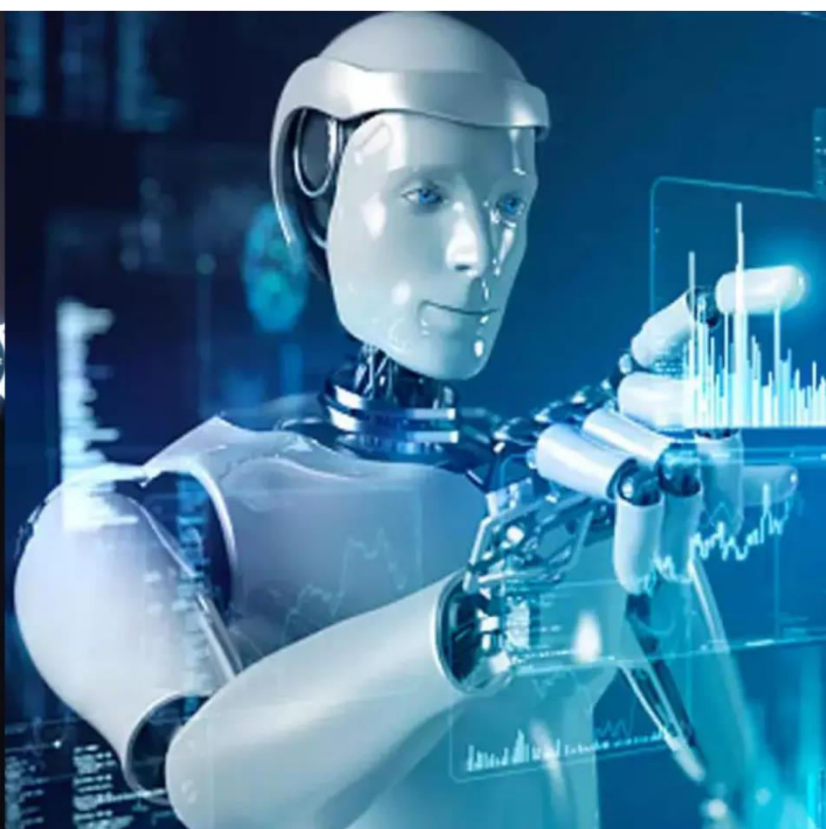




International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 9.935

Volume 15, Issue 10, October 2026

AI in Medical Diagnosis System Using Symptom-Based Machine Learning and Medical Image Analysis

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ABSTRACT: Early identification of possible health conditions can help people understand symptoms and seek appropriate medical evaluation. This paper presents an AI in Medical Diagnosis System, a web-based prototype intended to support preliminary health-information assessment through symptom-based prediction and medical-image classification. The application uses a Flask backend to receive user inputs, applies a machine-learning model to symptom data, and uses a TensorFlow/Keras image model for supported image uploads. The predicted category is then presented with general information mapped from a treatment-information file. The system combines multiple input paths in one interface and demonstrates how machine learning can be integrated into a web application. The prototype is an educational decision-support tool, not a clinically validated diagnostic system. Its reliability depends on dataset quality, model validation, image suitability, and clear communication of uncertainty. Predictions must not replace examination or advice from a qualified healthcare professional.

KEYWORDS: Artificial Intelligence, Medical Diagnosis, Machine Learning, Random Forest, Deep Learning, Medical Image Classification, Flask.

I. INTRODUCTION

Medical diagnosis may involve reviewing symptoms, medical history, laboratory findings, and medical images. Interpreting these different sources can be complex, and a computer-based tool may help organize information and demonstrate possible patterns in data. Machine-learning methods learn statistical relationships from examples, while deep-learning methods can learn representations from images and other complex inputs [1], [2].

The proposed AI in Medical Diagnosis System provides a web interface through which a user can submit symptoms or an image supported by the implemented model. The Flask application processes the request, invokes the relevant prediction model, and displays a predicted category with associated general information. A symptom-based classifier and an image-classification model are treated as separate pathways because they use different input formats and require different training and evaluation procedures.

The objective is to demonstrate an integrated prototype for educational use. The system does not establish a medical diagnosis, prescribe an individual treatment, or determine clinical urgency. Any health-related output must be interpreted cautiously and confirmed by a healthcare professional.

II. LITERATURE SURVEY

Shen, Wu, and Suk reviewed deep learning methods for medical image analysis and described their use in computer-assisted image interpretation, including classification and other image-analysis tasks [1]. Their review provides background for using a trained image model in the image-input part of this project. Image-model performance, however, depends on the target task, training data, and the similarity between training images and images encountered during use.

Sarvamangala and Kulkarni surveyed convolutional neural networks (CNNs) for medical image understanding [2]. CNN-based approaches are useful when relevant patterns are spatially distributed across an image. This supports the

general design choice of using a deep-learning model for image inputs, but does not establish the accuracy of the specific model used in this prototype.

Aggarwal and colleagues conducted a systematic review and meta-analysis of deep-learning diagnostic accuracy in medical imaging [3]. Their work reported variation across specialties and study methods, emphasizing that results from one dataset or task cannot automatically be generalized to another. Accordingly, this project should report measured performance only after evaluating its own held-out test data.

Breiman introduced Random Forests as an ensemble learning method that combines multiple decision trees [4]. Random Forest can be used for structured features such as symptom indicators, provided the data are appropriately prepared and the model is evaluated. For this project, symptom-based prediction and image-based prediction should be evaluated separately because their input data and error patterns differ.

The World Health Organization's guidance on ethics and governance of AI for health highlights the importance of safety, transparency, accountability, inclusion, and human oversight when AI is used in health-related settings [5]. These considerations are relevant to the project's user interface, data handling, and presentation of predicted results.

III. METHODOLOGY / APPROACH

A. System Architecture

The prototype follows a browser–backend–model workflow. The user interacts with a web page, and the Flask backend receives the selected input. For symptom prediction, symptom features are arranged in the format expected by the trained classifier. For image prediction, the uploaded file is checked and preprocessed to match the image model's expected input dimensions and representation. The corresponding model generates a predicted class, and the application displays the result with general information associated with that class.

The described implementation uses Python and Flask for request handling, a symptom-classification model intended to use Random Forest, a TensorFlow/Keras image model, and a treatment-information mapping stored separately (for example, in a JSON file). The exact supported diseases, preprocessing steps, and model versions should be documented from the final working code and training files.

B. Application Workflow

- 1) The user opens the web application and chooses the symptom-based or image-based prediction option.
- 2) For symptom prediction, the user selects or submits symptoms supported by the application.
- 3) For image prediction, the user uploads an image in an accepted file format.
- 4) The Flask backend validates the request and prepares the input for the corresponding model.
- 5) The selected model returns a predicted class or disease category.
- 6) The application retrieves relevant general information from its configured mapping and displays the output.
- 7) The user is advised to treat the result as preliminary information and consult a qualified healthcare professional.

C. Evaluation Plan

Evaluation should use a held-out test set that was not used to train the models. For symptom classification, useful measures include accuracy, precision, recall, F1-score, and a confusion matrix. For image classification, the same measures may be reported where appropriate, along with per-class results and checks for class imbalance. The evaluation should also test invalid inputs, unsupported file types, empty submissions, failed predictions, and server errors. Performance values must be calculated from actual tests; they should not be estimated or copied from other papers.

IV. RESULTS AND DISCUSSION

The prototype demonstrates an application structure for connecting a web interface to separate symptom and image prediction workflows. The symptom pathway is intended to process structured symptom features, while the image pathway processes uploaded image data. A treatment-information mapping can help present consistent general text alongside the model output. These are implementation capabilities, not evidence of clinical effectiveness.

No verified numerical accuracy, precision, recall, F1-score, sample size, or clinical validation results were provided for this paper. Therefore, no quantitative performance claim is made. Before presenting measured results, the team should record the dataset source, class distribution, training/test split, model configuration, preprocessing steps, test metrics, and examples of prediction errors. A model can appear successful on familiar examples while performing poorly on new images, different populations, or data collected in other settings.

Important limitations include possible dataset bias, incorrect or incomplete user inputs, image-quality variation, model overfitting, and mismatch between the training data and real-world use. Treatment text should be presented as general information rather than a personalized treatment recommendation. User data and uploaded images should be handled securely, and any external-service credentials should be kept out of public source repositories.

V. CONCLUSION

This paper describes an AI in Medical Diagnosis System that integrates symptom-based machine learning and medical-image classification through a Flask web application. The design illustrates how separate models can be connected to a common interface and how predicted categories can be linked to general health information. The prototype should be considered an educational decision-support demonstration rather than a medical diagnostic service. Future work should include reproducible testing, independent validation, per-class performance reporting, improved input checks, privacy safeguards, and review by qualified healthcare professionals before any real-world clinical use.

VII. ACKNOWLEDGMENT

The authors thank the faculty and project guide, Mrs. Pushpa S Tembad, M.Tech, of the Department of Computer Science and Engineering, STJ Institute of Technology, Ranebennur, for guidance and support.

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