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Deep Learning-Based Cervical Cancer Screening and image classification

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ABSTRACT: Screening for cervical cancer helps to catch abnormal changes in the cervix at an early stage, but its reliability can suffer from poor image quality, a limited supply of specialists, and subjective differences between observers. This paper describes an AI-driven screening system that applies a DenseNet121 deep learning network to classify cervical colposcopy images. Images from the Intel & MobileODT Cervical Cancer Screening Dataset are preprocessed and augmented before they reach the model, which labels every image as either Normal or Abnormal. The classifier is embedded in CerviCare, a web application that lets users upload an image and receive a prediction through a simple workflow, together with other application features that support preliminary screening. According to the project documentation, the DenseNet121 classifier reaches an overall test accuracy of 91.11%. The system is intended as a prototype that assists screening and must not be treated as a substitute for diagnosis by a medical professional.

KEYWORDS: Cervical cancer, cervical screening, deep learning, DenseNet121, colposcopy images, medical image classification, artificial intelligence.

I. INTRODUCTION

Early screening is one of the most useful ways to spot abnormal changes in the cervix before they progress, which is why cervical cancer remains a significant public-health concern. Traditional screening depends on trained health professionals, and its outcomes may vary with the clarity of the captured images, the number of specialists who are available, and the differing judgments of individual examiners. These limitations have pushed researchers toward artificial intelligence and deep learning as aids for computer-assisted analysis of cervical images.

This work introduces an AI-based cervical cancer screening system built on deep learning with the DenseNet121 architecture. The network sorts colposcopy images of the cervix into two classes, Normal and Abnormal. The images are taken from the Intel & MobileODT Cervical Cancer Screening Dataset and are preprocessed before classification. The resulting system, called CerviCare, couples the trained model with a web application so that screening follows a clear and organized sequence. A user submits a cervical image, and the application returns a preliminary classification. The system is built to support screening and is not intended to take the place of a medical professional's diagnosis.

The main contributions of this work are as follows:

- A DenseNet121 classifier applied to cervical images.
- A preprocessing and augmentation stage that prepares images as model input.
- Embedding of the trained model in a web-based screening application.
- A first-level Normal or Abnormal decision for each submitted cervical image.

II. LITERATURE REVIEW

A growing body of work applies deep learning to cervical cancer screening and image classification. Cho et al. [1] examined pretrained CNN models for classifying cervical neoplasms from colposcopic photographs. Luo et al. [2] put forward an approach that merges features from several CNNs to identify precancerous cervical lesions, and Liu et al. [3] built a ResNet-based method that combines image features with clinical information.

Other groups have taken different routes. Rahaman et al. [4] introduced DeepCervix, which fuses deep features of different kinds, whereas Chandran et al. [6] studied an ensemble of CNNs for colposcopy images. Some studies also pair U-Net segmentation with classification so that the analysis concentrates on the relevant cervical regions [10].

Transfer learning with pretrained CNN architectures has likewise been used for cervical image classification [8]. Such models supply helpful feature representations, especially when medical datasets are small. Still, the reported results may not generalize well, because the studies differ in datasets, image acquisition conditions, class definitions, and validation protocols.

Overall, earlier studies indicate that deep learning can yield useful outcomes for classifying cervical images, yet narrow data diversity and the lack of external validation continue to be major concerns. In light of this, the present work adopts DenseNet121 as a practical deep learning backbone for binary classification of cervical colposcopy images.

Table 1 compares the studies reviewed above in terms of objective, method, dataset, findings, limitations, and the research gap each one leaves open.

Table 1: Summary of related literature

Ref. No.	Author(s)	Year	Objective	Methodology	Dataset / Tool	Key Findings	Limitations	Research Gap
[1]	Cho et al.	2020	Classification of cervical neoplasms	Pretrained CNN models	Colposcopy images	CNN models achieved useful classification results	Results vary with the task and dataset	Stronger validation is needed
[2]	Luo et al.	2020	Identifying cervical precancerous lesions	Integration of features from multiple CNNs	Colposcopy images	Merging CNN features gave a richer feature representation	Higher model complexity	More efficient deep learning approaches are required
[3]	Liu et al.	2021	Classifying cervical lesions from images together with clinical data	ResNet model that includes clinical features	Colposcopy images + clinical data	Adding clinical data to image features raised classification quality	Data came from a restricted setting	Wider external validation is needed
[4]	Rahaman et al.	2021	Classification of cervical images	Fusion of hybrid deep features	SIPaKMeD, Herlev	Fused deep features gave an effective image representation	Imbalanced and varying data	Validation across varied datasets is needed
[6]	Chandran et al.	2021	Classification of cervical colposcopy images	VGG19 with an ensemble of CNNs	Colposcopy images	Ensembling boosted classification results	Little external validation	Cross-dataset evaluation should be strengthened

Ref. No.	Author(s)	Year	Objective	Methodology	Dataset / Tool	Key Findings	Limitations	Research Gap
[9]	Habtemariam et al.	2022	Detecting and classifying cervical lesions	YOLOv3-MobileNet and EfficientNet	Colposcopy and pathology images	Detection and classification were combined	Processing in several stages adds complexity	Simpler, integrated screening systems are needed
[10]	Jiménez Gaona et al.	2022	Segmenting and classifying the cervical region	U-Net with SVM	Intel & MobileODT + clinical data	Segmentation directed attention to the relevant cervical areas	Segmentation increases computational cost	Efficient end-to-end approaches are needed
[8]	Kaur et al.	2025	Comparing transfer learning approaches for cervical image classification	Pretrained CNN models	SIPaKMeD, Herlev	Transfer learning delivered useful classification outcomes	Benchmark data may not reflect real clinical conditions	Real-world and external validation are needed

Looking across Table 1, a few patterns stand out. Most of the reviewed studies report useful results on their own data, yet the majority of them ask for stronger, wider, or external validation, which makes it hard to compare reported performance from one setting to another. Several of the approaches, namely feature integration, ensembles, and multi-stage detection or segmentation pipelines, gain accuracy at the price of extra complexity, and the research-gap column repeatedly points to a need for simpler, end-to-end systems that can be used in practice. These observations motivate the direction taken in this paper: a single DenseNet121 classifier packaged inside a complete web workflow.

III. PROPOSED METHODOLOGY

The proposed system relies on a deep learning approach for binary classification of cervical colposcopy images. The methodology comprises preparing the dataset, preprocessing the images, classifying with DenseNet121, training the model, and running inference. Input images are processed and enhanced before they reach the trained model, which then outputs a Normal or Abnormal prediction according to the image features it has learned. This pipeline offers a simple and well-organized route to AI-assisted screening of cervical images, and Figure 1 illustrates it.

3.1 Dataset

Training and testing images come from the Intel & MobileODT Cervical Cancer Screening Dataset, a collection of cervical colposcopy images. For this work the images are grouped into two classes, Normal and Abnormal, so the task is handled as binary classification.

3.2 Image Preprocessing and Augmentation

Before an image enters the network it is resized to 288×288 pixels and normalized. Augmentation then adds variety to the data through rotation, flipping, zooming, and brightness changes, while CLAHE (contrast-limited adaptive histogram equalization) improves the visibility of local detail in the image.

3.3 DenseNet121-Based Classification

DenseNet121 serves as the backbone of the classifier. It extracts features from the preprocessed image and carries out the classification. In a DenseNet, every layer receives the feature maps of all the layers before it, which encourages feature reuse and keeps the number of parameters moderate. The model takes a 288×288 RGB image as input and returns a binary prediction, Normal or Abnormal.

3.4 Test-Time Augmentation and Prediction

During inference, test-time augmentation (TTA) creates several transformed versions of the submitted image, and the predictions made on these versions are combined into one final prediction. The result, together with a confidence score, is then displayed to the user in the web application.

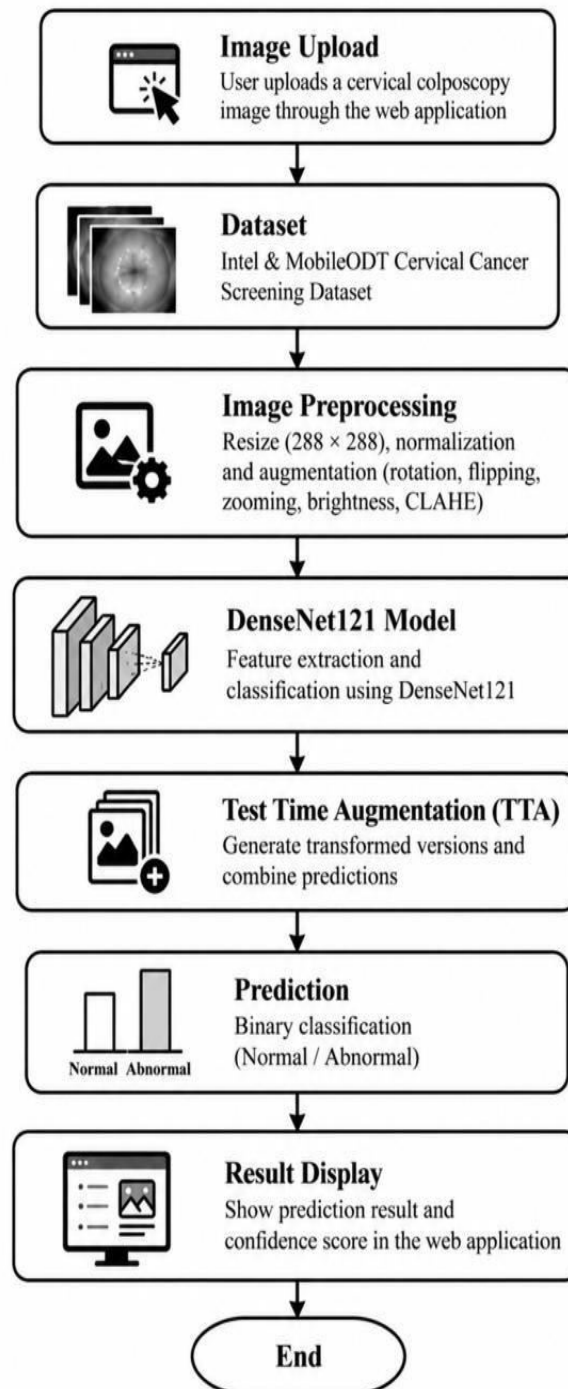


Figure 1: Overall workflow of the AI-based cervical cancer screening system proposed in this work.

IV. SYSTEM ARCHITECTURE

CerviCare is organized as a multi-layer architecture made up of a presentation layer, an application layer, an AI processing layer, and a database layer. Access is role-based, with separate roles for patients, doctors, ASHA workers, administrators, and screening units, and the frontend talks to the backend services through REST APIs.

4.1 Presentation Layer

The presentation layer is built with React, Vite, TypeScript, and Tailwind CSS. It offers role-specific dashboards and screens for patient registration, cervical image upload, viewing screening results, doctor referrals, appointments, and further system functions.

4.2 Application Layer

Node.js and Express.js power the application layer, which exposes REST APIs for authentication, patient management, analyses, doctors, hospitals, assignments, appointments, and chat. User authentication and role-based access control rely on JSON Web Tokens (JWT).

4.3 AI Processing Layer

Python and Flask implement the AI processing layer, which hosts CervixNet121, the DenseNet121-based model for classifying cervical images. The model accepts an RGB image of 288×288 pixels and returns a binary prediction, Normal or Abnormal.

4.4 Database Layer

System data is stored and managed in MongoDB through Mongoose. Its collections cover users, patients, analyses, assignments, appointments, chats, and hospitals.

4.5 System Workflow

A user opens the CerviCare web application and submits a cervical image for screening. The AI service processes the image with the DenseNet121 model and produces a Normal or Abnormal prediction, which is sent back to the application and shown in the relevant user interface. Figure 2 shows the overall architecture, and Table 2 lists the technologies used.

Table 2: Technology stack

Component	Technology
Frontend	React 19, Vite, TypeScript, Tailwind CSS
Backend	Node.js, Express.js
Database	MongoDB, Mongoose
AI Engine	TensorFlow / Keras, DenseNet121
AI API	Python, Flask, Flask-CORS
Authentication	JWT
Image Processing	Pillow, NumPy

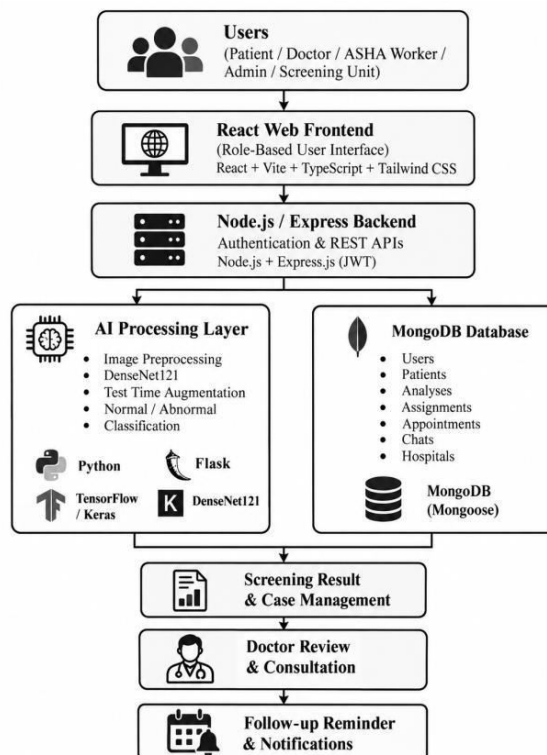


Figure 2: General architecture of the proposed CerciCare AI-based cervical cancer screening system.

V. EXPERIMENTAL RESULTS AND DISCUSSION

To check how the whole screening workflow behaves in practice, a working prototype of the proposed AI-based cervical cancer screening system was built. The web application receives cervical colposcopy images and passes them to the DenseNet121-based AI model. Each image is preprocessed and assigned to the Normal or Abnormal class, and the application then shows the prediction along with its confidence score.

In the project's own evaluation, the model reached an overall test accuracy of 91.11%, with a precision of 0.89, a recall of 0.91, a specificity of 0.90, and an F1-score of 0.90. These figures suggest that the implemented pipeline learned visual features that are useful for binary classification of cervical images. Nonetheless, they come from the internal test set only, so external and patient-wise validation is still needed for a wider assessment.

5.1 Performance Evaluation

The DenseNet121-based model was assessed using standard classification metrics. As reported by the project, it attained 91.11% overall test accuracy on the internal test set, along with a precision of 0.89, a recall of 0.91, a specificity of 0.90, and an F1-score of 0.90. Together, these metrics describe how well the model separates Normal cervical images from Abnormal ones. Table 3 lists the values, and Figure 3 presents the same metrics graphically, together with AUC, TPR and TNR.

For readers less familiar with these measures: accuracy is the share of all test images that are classified correctly. Precision is the share of positive predictions that turn out to be right, recall (sensitivity) is the share of actual positive cases that the model finds, and specificity is the share of actual negative cases that it correctly rejects. The F1-score is the harmonic mean of precision and recall, so it balances the two. In Figure 3, TPR and TNR denote the true positive and true negative rates, which correspond to sensitivity and specificity, and AUC summarizes how well the model separates the two classes across all decision thresholds.

Table 3: Performance evaluation of the proposed model

Parameter	Result
Overall Test Accuracy	91.11%
Precision	0.89
Recall (Sensitivity)	0.91
Specificity	0.90
F1-Score	0.90
Correctly Classified Normal Images	567
Correctly Classified Abnormal Images	559
Total Test Images	1,325

Reading the results together, sensitivity (0.91) and specificity (0.90) lie close to each other, which suggests that the model recognizes Abnormal and Normal images with similar reliability instead of favoring one class. Precision (0.89) is marginally lower than the other measures, so a small share of the images the model flags may turn out to be false alarms; in a screening setting this is tolerable because every flagged case is passed on for review by a doctor. These remarks apply only to the internal test set described above.

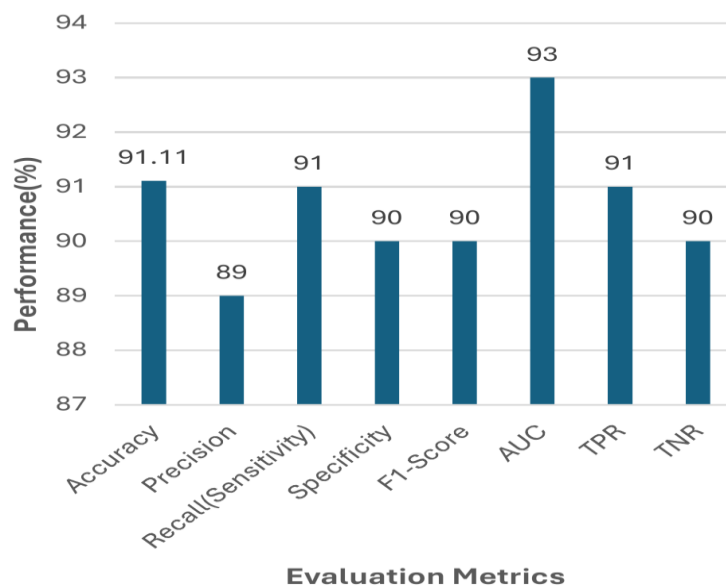


Figure 3: Model performance across the evaluation metrics.

5.2 Comparative Analysis

CerviCare brings together AI-based cervical image screening, automatic Normal/Abnormal classification, patient record management, and doctor review in one web-based platform. This gives screening a structured flow and makes preliminary assessment more efficient. Table 4 compares the proposed system with existing systems.

Table 4: Comparison with existing systems

Feature	Existing Systems	Proposed System
Online Image Screening	Limited	✓
AI-based Image Classification	Limited	✓
Automated Normal/Abnormal Prediction	Limited	✓
DenseNet121-based Classification	✗	✓
Image Preprocessing	✗	✓
Screening Result Display	Limited	✓
Patient Record Management	✓	✓
Doctor Review	✓	✓

5.3 Limitations of the Current Evaluation

The figures reported here describe a prototype that was evaluated on a single internal test set. They say little about how the model would behave on images captured with other devices, in other clinics, or from other groups of patients, and external as well as patient-wise validation has still to be carried out. For this reason, the accuracy of 91.11% is best read as an indication of feasibility rather than as proof of clinical performance. CerviCare is therefore positioned as a screening-support tool: its Normal/Abnormal output is meant to help prioritize cases for review by a doctor, not to confirm or rule out disease.

VI. PROTOTYPE TESTING AND INTERFACE RESULTS

The prototype was tested to confirm that the CerviCare system works as intended. Testing covered uploading a cervical image, preprocessing it, classifying it with DenseNet121, generating a prediction, and showing the result in the web application. The system handled the submitted images without trouble and produced Normal or Abnormal screening results.

The full workflow was also checked end to end, from image submission through to result generation. The tests showed that the main components of the system behaved as expected and could deliver a structured, AI-assisted screening workflow. The system is meant to assist preliminary screening and does not replace clinical diagnosis by a professional. Figures 4 to 18 show the principal screens of the application in the order in which the different user roles reach them.

6.1 Landing Page and Administrator Module

Figure 4 shows the landing page, from which a visitor can begin screening or create an account. After signing in, an administrator reaches a profile page with summary figures (Figure 5) and tabs for adding hospitals, doctors, ASHA workers, and screening units (Figures 6 to 8).

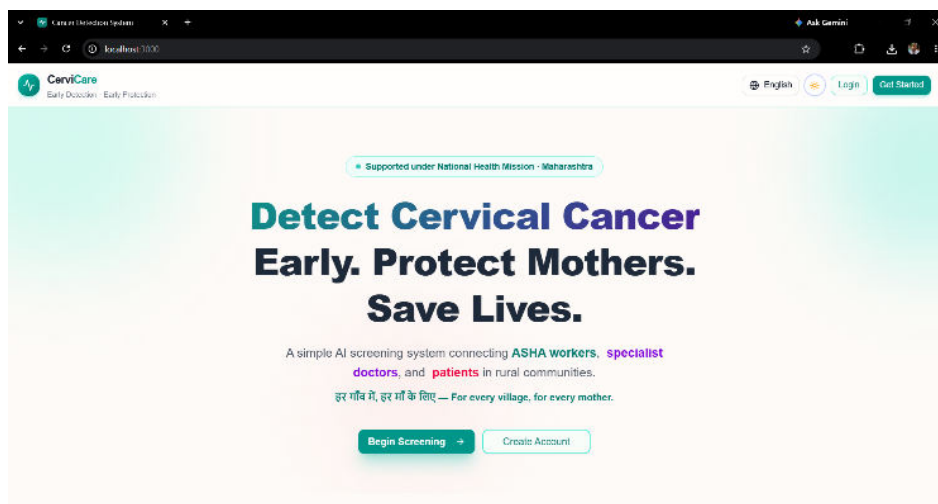


Figure 4: Landing page of the CerviCare cervical cancer screening system.

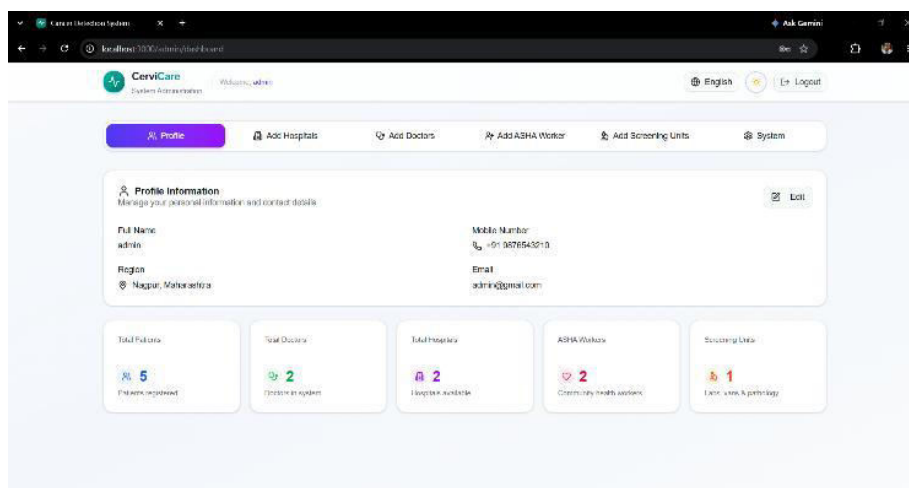


Figure 5: Admin profile screen of the CerviCare system.

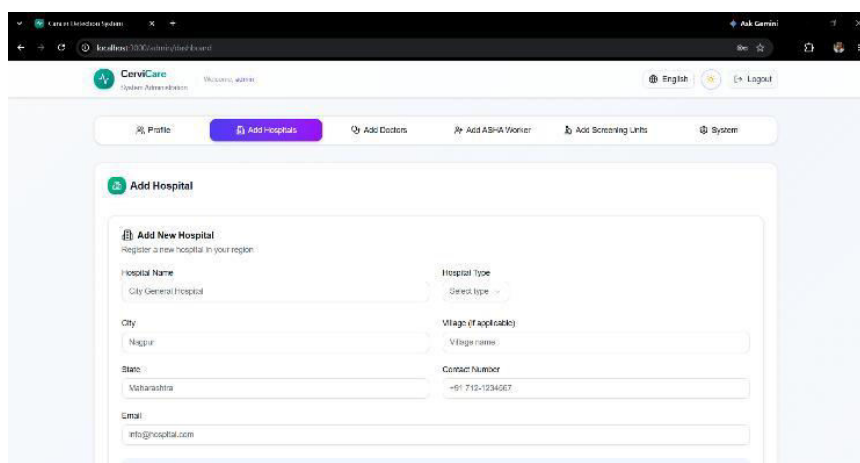
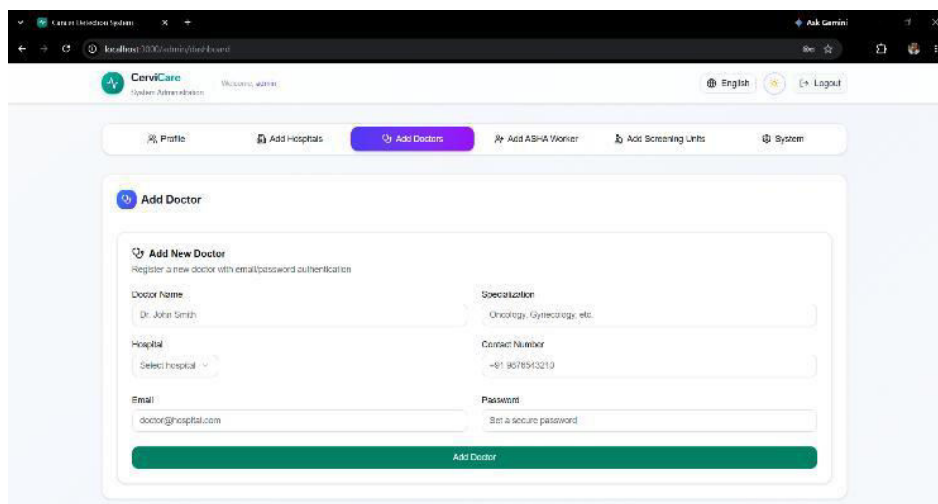


Figure 6: Admin interface for adding hospitals.

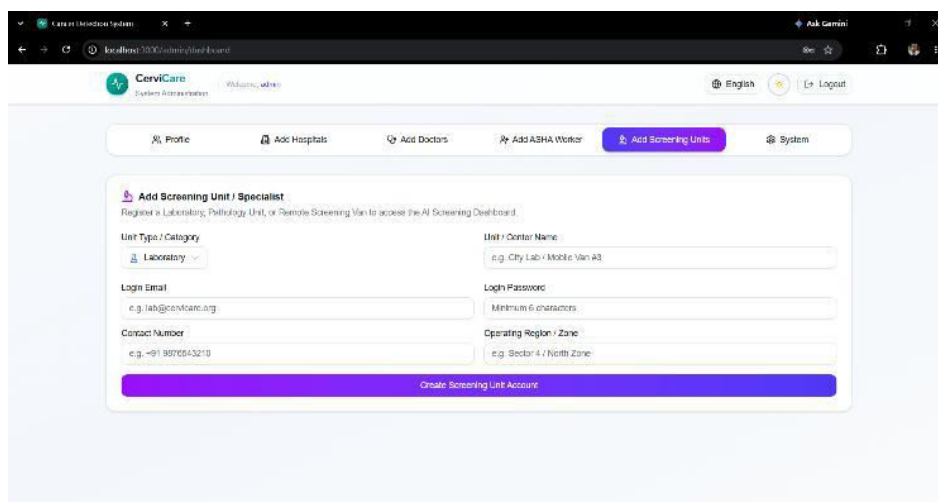


The screenshot shows the 'Add Doctor' form in the CerviCare System Administration interface. The form is titled 'Add New Doctor' and includes instructions: 'Register a new doctor with email/password authentication'. The form fields are as follows:

- Doctor Name:** Dr. John Smith
- Specialization:** Oncology, Gynecology, etc.
- Hospital:** Select hospital (dropdown menu)
- Contact Number:** +91 9876543210
- Email:** doctor@hospital.com
- Password:** Set a secure password

A green 'Add Doctor' button is located at the bottom of the form.

Figure 7: Admin interface for adding doctors.



The screenshot shows the 'Add Screening Unit / Specialist' form in the CerviCare System Administration interface. The form is titled 'Add Screening Unit / Specialist' and includes instructions: 'Register a Laboratory, Pathology Unit, or Remote Screening Van to access the AI Screening Dashboard'. The form fields are as follows:

- Unit Type / Category:** Laboratory (dropdown menu)
- Unit / Center Name:** e.g. City Lab / Mobile Van A3
- Login Email:** e.g. lab@cervicare.org
- Login Password:** Minimum 6 characters
- Contact Number:** e.g. +91 9876543210
- Operating Region / Zone:** e.g. Sector 4 / North Zone

A purple 'Create Screening Unit Account' button is located at the bottom of the form.

Figure 8: Admin interface for adding ASHA workers.

6.2 Doctor and ASHA Worker Modules

Doctors sign in with an email ID and password to reach a dashboard with their profile details (Figure 9). ASHA workers use a separate portal (Figure 10) with options for registering patients, contacting doctors, chatting with patients, reading guidelines, and tracking referrals. A registered patient receives a generated patient ID (Figures 11 and 12), and the worker can refer the patient to a selected doctor (Figure 13) and communicate with patients and doctors through the built-in chat (Figures 14 and 15).

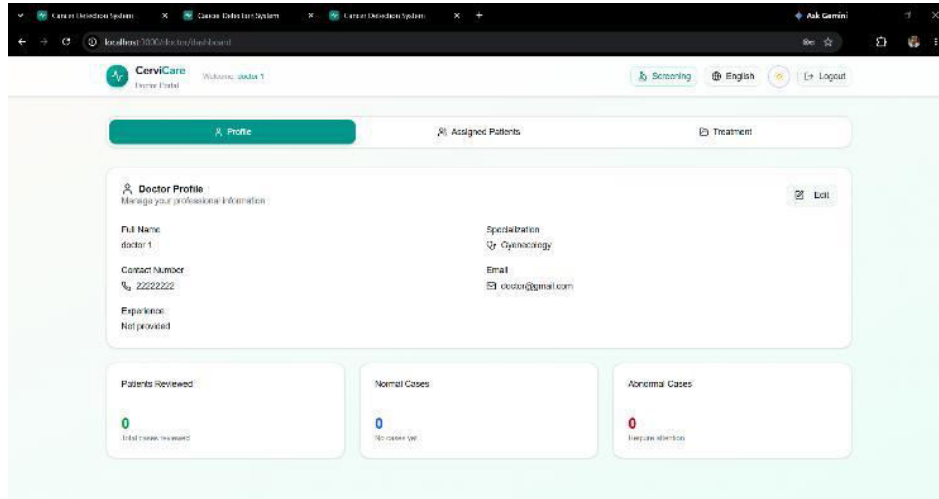


Figure 9: Doctor's page, reached by logging in with an email ID and password.

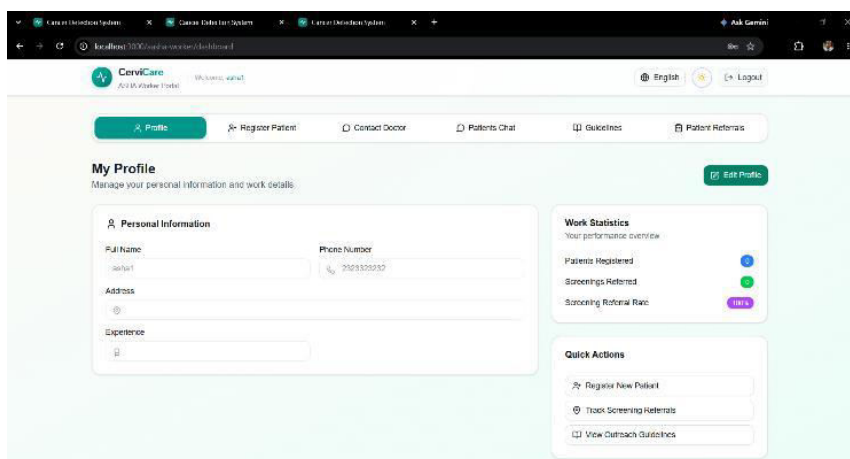


Figure 10: Portal page for ASHA workers.

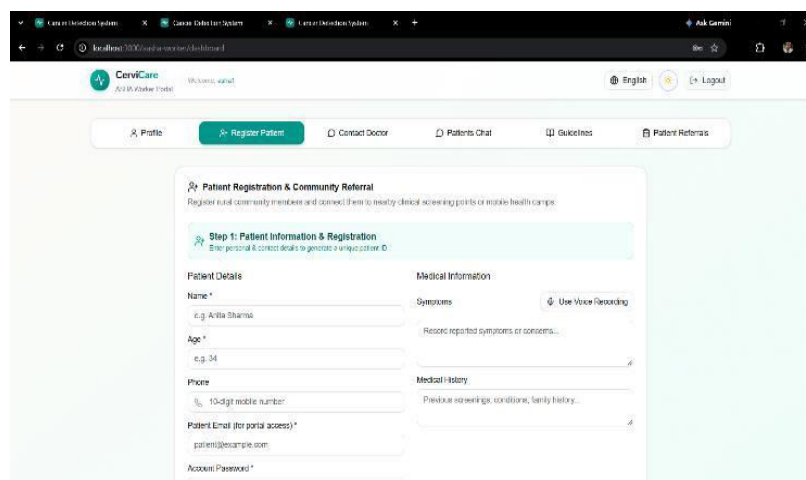


Figure 11: Patient registration form used by an ASHA worker.

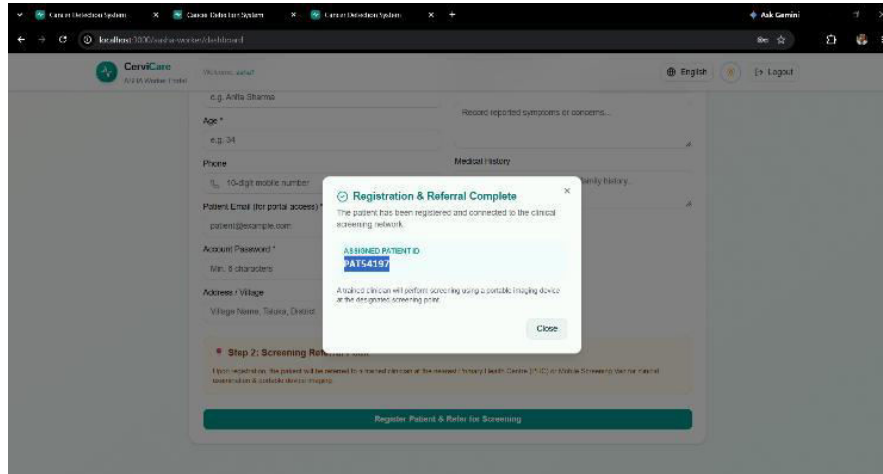


Figure 12: Patient details saved and a patient ID generated.

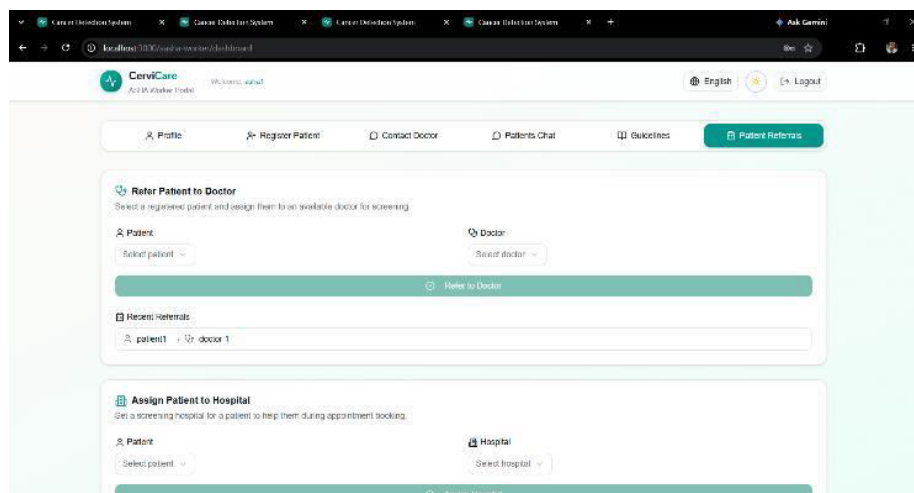


Figure 13: ASHA worker referring a patient to a selected doctor.

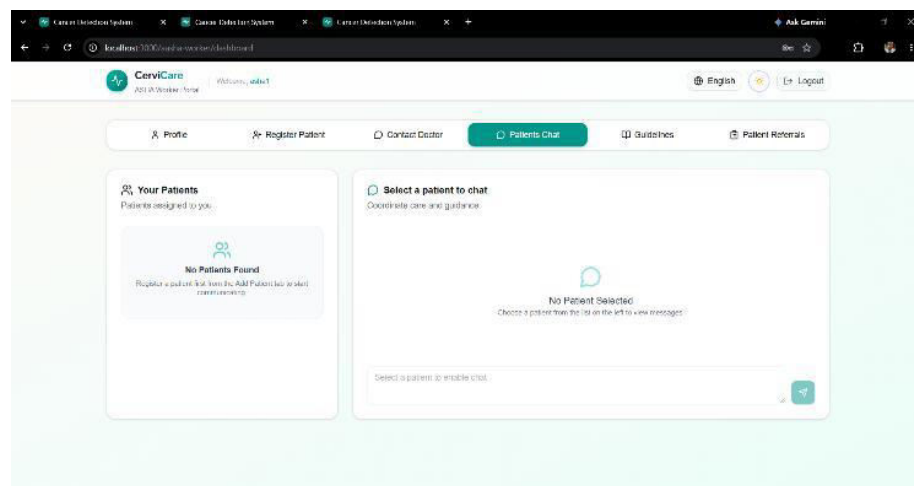


Figure 14: ASHA worker chatting with a patient.

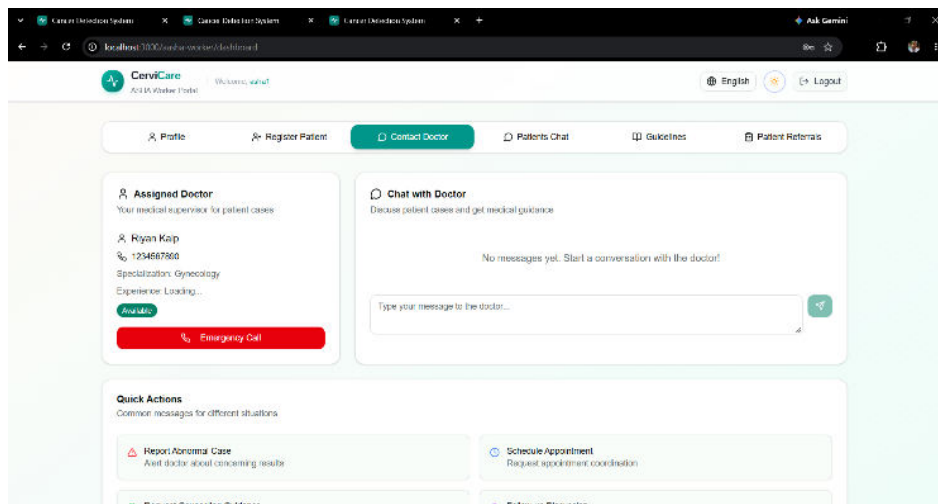


Figure 15: ASHA worker chatting with a doctor.

6.3 AI-Based Image Analysis and Report

A doctor opens the analysis screen (Figure 16), enters the patient ID, and uploads a colposcopy image (Figure 17). When Run Analysis is selected, the image is sent to the AI service, and the page then shows the predicted class, the confidence score, and suggested recommendations, with an option to print the report (Figure 18).

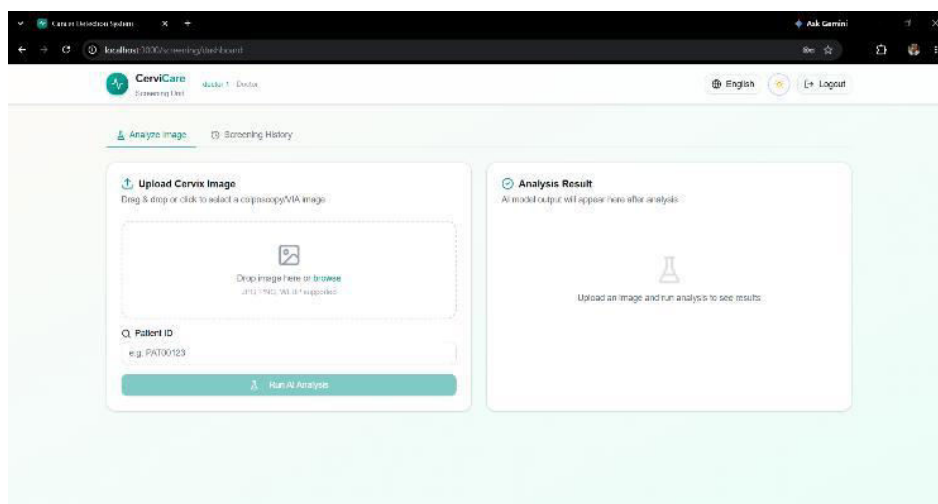


Figure 16: Doctor analysing an image with the model to obtain a prediction.

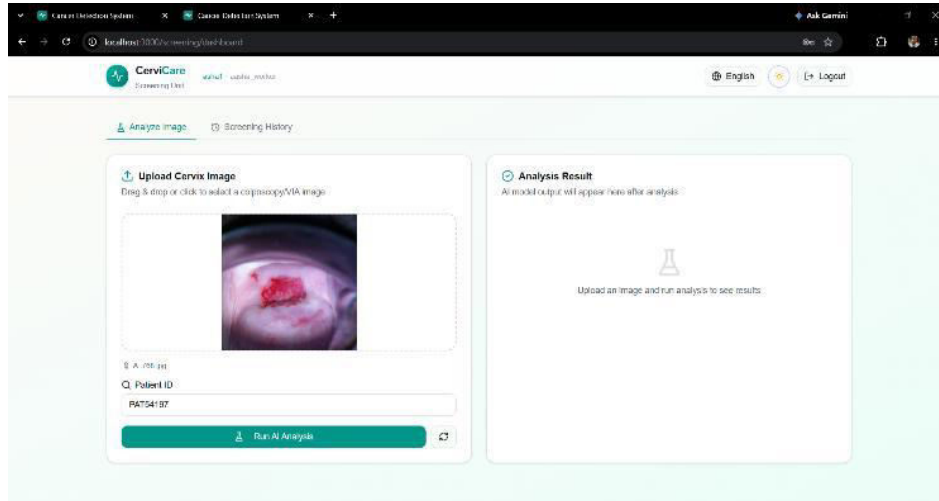


Figure 17: Image uploaded and ready for the Run Analysis action.

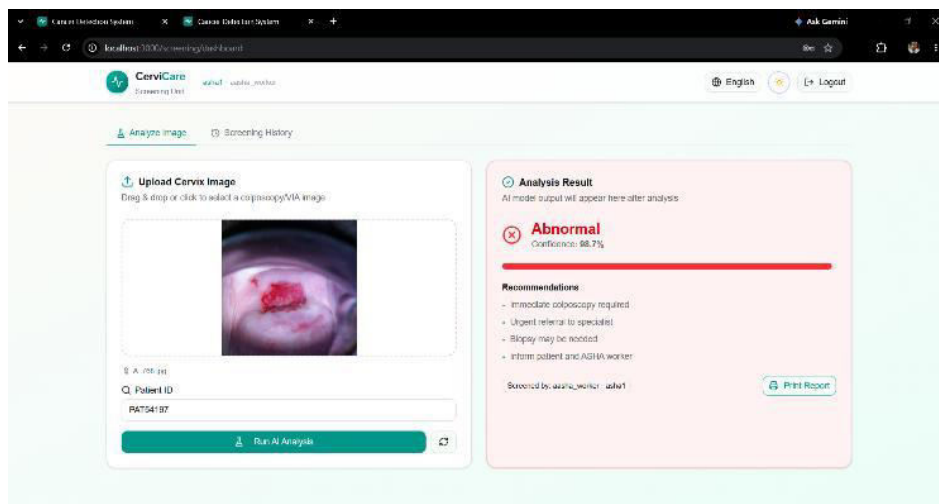


Figure 18: Final report: the model's Normal/Abnormal result for the uploaded image.

VII. CONCLUSION AND FUTURE WORK

This paper described an AI-based cervical cancer screening system that combines DenseNet121 with the CerviCare web application to provide preliminary classification of cervical colposcopy images. The system offers a structured workflow covering image submission, Normal/Abnormal classification by AI, result display, patient management, and review by a doctor. The project-reported test accuracy of 91.11% shows the potential of this approach for AI-assisted screening of cervical images.

Possible extensions include multi-class classification of CIN grades, explainability through Grad-CAM, validation on a wider range of external data, PDF report generation, offline support, and additional regional languages.

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