Empowering Future Engineers: Educational Journey From AI Fundamentals to Healthcare Innovations

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***Abstract*—This research-to-practice paper details implementing an educational approach designed to equip undergraduate students with the skills to develop healthcare applications and contribute to this domain using Medical AI by bridging the gap between the AI and the medical domain. This gap includes three challenges: medical data acquisition, strict privacy regulations in handling medical data, and a disconnect between the medical domain's requirements and AI's capabilities. To handle these challenges, We structured our educational approach into three phases: The first one is the educational AI stack which includes five learning stages, the second one is the medical foundation stack, which includes two working stages and the third one is system development, deployment, operation and testing. We implemented this approach within three Senior Design Projects focused on diagnosing skin cancer, breast cancer predication, and assessing allergy risks based on personal and biological data. The approach begins with a foundational AI stack, including TensorFlow, Scikit-Learn, and Keras, emphasizing transfer learning and model architecture selection customization. The second phase included the medical data acquisition process, NDA (Non-disclosure agreement) signing by the participants in these projects, and data handling, preprocessing, model selection, and training. The final phase included systems development, Deployment, and operation and testing. Students achieved significant results, including a 94% accuracy rate in skin cancer detection and over 85% precision in breast cancer prediction, including the tumor grade, stage, recurrence, and survival in the second project. And an 88% accuracy in allergy prediction using biological information, including Skin color and skin condition. They integrated the trained models with three developed web applications for the end users. Following the integration process, they deployed these applications into AWS and GCP. They compared the trained models between these two cloud platforms to determine their AI models' most effective deployment environment considering the model accuracy and cost. As a final step, the students tested the deployed applications within five stages, including the Go-live test, system performance, user satisfaction, model accuracy, and security status. Our approach aligns with ABET accreditation standards, focusing on the practical application of medical AI.**

***Index Terms*—Educational AI, AI Stack, Keras, Healthcare Innovations, Skin Cancer detection, Allergy Detection, HIPAA, ABET Accreditation, System Development, AWS, GCP.**

I. Introduction

Artificial intelligence (AI) is transforming many sectors, including healthcare, by offering innovative solutions, including advanced risk profiling using Machine Learning for cancer types and cost-effective, scalable, and reliable solutions that significantly enhance diagnostic. Unlike conventional programming and traditional approaches, which rely on explicit instructions to perform only well-defined tasks, AI learns from data, adapting and evolving to meet complex challenges. This dynamic capability sets AI apart and highlights the need for specialized educational approaches and techniques. It's about learning and understanding the importance of rapidly evolving in the medical AI domain.

Despite these promising advantages, bridging the gap between the AI and medical stacks presents many challenges. One of these challenges is Strict privacy regulations. In the United States, the Health Insurance Portability and Accountability Act (HIPAA) imposes substantial barriers to accessing and utilizing medical data for AI training and applications. Moreover, there is a disconnect between the medical domain's requirements and AI experts' capabilities. Medical professionals often need more in-depth knowledge of AI's potential and limitations, while AI technologists typically need to understand medical protocols and processes sufficiently.

To bridge this gap, we designed our approach with six teams of senior design students (36 students) from the software engineering department at Iowa State University. We help students to understand the complexities of Medical AI and prepare them to contribute effectively to this field by working on three healthcare projects (Skin cancer project, Pathology project, and Allergy project). This paper focuses on student learning and development in healthcare innovation, focusing on healthcare's ethical and regulatory aspects.

Our approach is aligned with ABET accreditation standards, mainly focusing on student outcomes and the ability to apply knowledge of mathematics, science, and engineering (Criterion 3, Outcome 1), the ability to design and conduct experiments, as well as analyze and interpret data (Criterion 3, Outcome 2), and the ability to create a system, component, or process to meet desired needs within realistic constraints (Criterion 3, Outcome 3). We aim to develop students' theoretical understanding of Medical AI and its practical applications in real-world settings. While our students may wait to make cutting-edge innovations, they build a strong foundation for future contributions to the field.

We structured our approach into three phases: the educational AI stack and the medical foundation stack, system development, deployment, operation, and testing. The Educational AI stack phase included three stages, starting with the AI Fundamentals Stack: Hardware, TensorFlow, Scikit Learn, and Keras (deep learning API developed by Google for implementing neural networks), and advancing through more complex tools. Following this stage, mastering Keras for Project completion and model training techniques, transfer learning, which is a technique that reuses a model pre-trained on one task to improve performance on related tasks.

The second phase included (domain problems and medical data collection, acquisition, handling, preprocessing, model selection, and training stages). The third and final phase included five stages: system architecture design, system development, integration of AI Models, system deployment, and system operation. Each of these stages included sub-stages detailing the process of each stage.

For the medical data collection stage for the skin cancer project, We used The International Skin Imaging Collaboration (ISIC) dataset, which is an open-source dataset for training, testing, and lesion classification. We used the Fourier transform infrared (FTIR) spectroscopy for the breast cancer project. This chemical imaging technique can analyze and identify the biomarkers in tumor tissues or blood serum samples.

II. Literature Review

This literature review expands on earlier research investigating how AI might be incorporated into educational approaches, mainly in education programs.

Flores-Alonso et al. (2022) discuss the limitations and opportunities of introducing AI concepts to undergraduate engineering students. Their work emphasizes the necessity of a multidisciplinary approach, blending engineering principles with AI technology to solve complex real-world problems. The paper highlights several case studies where students applied AI to solve engineering problems, suggesting a model that could be replicated in healthcare education to enhance diagnostic and treatment decision processes.

Vojinovic et al. (2022) explore the effectiveness of tiered assignments in AI labs, aiming to improve student motivation and learning outcomes through structured task complexity. This educational approach could be instrumental in healthcare AI education, where the complexity of medical data and the critical nature of healthcare outcomes demand a carefully calibrated learning curve. By implementing tiered learning assignments, educators can gradually introduce healthcare professionals to sophisticated AI tools, ensuring comprehensive understanding and effective application in clinical settings. [2].

A. Rajkomar, J. Dean. (2019) provided a comprehensive review of using AI approaches in solving healthcare challenges by emphasizing the potential of improving diagnostic accuracy and patient outcomes using AI. This research underscores the importance of integrating AI technologies in medical settings and highlights the challenges, including data acquisition and the need for handling medical data and ethical guidelines to protect patient privacy [3].

III. Projects Structure

We organized our healthcare projects into three projects. we had six Senior Design (SD) teams, so we assigned two SD teams to each project, resulting in all six teams focusing on the three distinct projects.

A. *Skin Cancer Prediction Project*

Teams 1 and 2 worked on the Skin Cancer Prediction project. They aimed to develop a deep-learning model that accurately identifies malignant skin lesions.

1) Objectives:

- Develop an AI model to accurately classify skin images as benign or malignant.
- Develop a client application for end users and integrate it with the trained AI model.
- Deploy and compare between cloud providers: After integrating the trained model and the client application, they were tasked to deploy the full application to two cloud providers, AWS and GCP, to assess the cost-effectiveness and efficiency of AI model deployment.
- Operate and test the deployed system regarding performance, security, and accuracy.

2) Phases:

- Data Collection: Gathered dermatological image data (ISIC Datasets) that has a representation of skin conditions.
- Model Training: Employed convolutional neural networks (CNNs) and other neural network (NN) tools to learn from the image data.
- Validation and Testing: Conducted rigorous testing to validate the accuracy and reliability of the AI model.
- Integration Phase: Integrated the AI model with the developed client application (web and mobile) to provide a complete application for end users.
- Deployment and Testing Phase: Deployed the integrated components (AI model, application, and database) to two different cloud providers (AWS, GCP) to assess the cost-effectiveness and efficiency of AI model deployment.

B. Accurate Cancer Prediction Using Pathology Data

Teams 3 and 4 focused on enhancing the accuracy of the breast cancer predictions for post-op cases, including the cancer grade, stage, recurrence, and survival, by analyzing encoded cell samples. This section details the project objectives and phases.

1) Objectives:

- Enhance the precision of breast cancer predictions using AI models that analyze encoded cell sample data.
- Develop a client application for end users that integrates with the AI model to provide intuitive interaction and result dissemination.
- deploy and compare the application across different cloud platforms, including AWS and GCP, to assess the cost-effectiveness and efficiency of the AI model.
- Operate and test the deployed application regarding performance, security, and accuracy.

2) Phases:

- Data Collection and Normalization: Fourier Transform Infrared Spectroscopy (FTIR) was used to extract spectral data from encoded cell samples of tumor slides (400 samples).
- Data Preprocessing and Feature Selection: Implemented peak signal analysis and selected the features to use in ML model training to handle the challenges posed by high-dimensional data, enhancing the model's accuracy and reducing computational load.
- AI Model Training: Trained machine learning models including Keras models, and random forest. Utilized the trained model to predict key patient outcomes, cancer stage, recurrence likelihood, and life expectancy, aiming to correlate encoded cell sample data with long-term health metrics.
- Integration Phase: Integrated the AI model with the developed client application to create an application for end users.
- Deployment and Testing Phase: Deployed the integrated components (AI model, client application, and database) to two different cloud providers (AWS, GCP).

C. Allergy Prediction Project

Teams 5 and 6 worked on predicting allergic reactions using skin data and other biological markers, including skin tone, skin condition, and date of birth.

1) Objectives:

- Develop predictive models to assess potential allergic reactions based on genetic and environmental factors.
- Create a client application as a web application for healthcare providers and patients to interact with the AI system.
- Deploy the application across different cloud platforms, including AWS and GCP.
- Operate and test the deployed system regarding performance, security, and accuracy.

2) Phases:

- Data Collection and Analysis: We collected people's data sets, including skin data and biological markers related to allergic responses.
- Data Preprocessing and Feature Selection: Loaded datasets from Excel files, including patients' biological data and skincare products with their ingredients. Combined patient information and allergen data into a single dataset. Removed unnecessary columns not used in the analysis, and included non-relevant personal details. Removed rows with blank cells, NaN (not-a-number) to ensure data are cleaned. Converted categorical data into a numerical format using One Hot-Encoding, transforming categorical variables into a binary matrix. Applied One Hot-Encoding to both skin conditions (input) and allergens (output) to prepare the data for machine learning models.
- AI Model Training: Trained machine learning models to analyze data and predict allergies, improving model sensitivity and specificity.
- Integration Phase: Integrated the AI model with the developed client application to create a seamless application for end users.
- Deployment and Testing Phase: Deployed, and tested the integrated components (AI model, application, and database) to two different cloud providers (AWS, GCP).

IV. Approach

We structured our approach into three main phases: AI educational Phase, which includes three stages. The second phase is the medical foundation phase, which includes two stages. The third phase is the system Development and Deployment phase, which includes five stages.

A. AI Educational Phase

This phase focuses on educating and working with the SD students on the foundation of AI, which includes the AI stack and preprocessing tools, encoding methods, and Model training techniques. This phase includes three stages.

1) AI Fundamentals Stack:

- First Stage: Hardware - This first stage introduces hardware requirements for AI, focusing on transitioning from CPUs to GPUs. It highlighted CPUs' failure to handle larger AI models by 2015 and solutions for this challenge. In addition, it provides a detailed comparison of different GPUs (GTX 1070, GTX 1080TI, RTX 2080TI) to illustrate the impact of hardware on AI training performance.
- Second Stage: TensorFlow - This stage involves hands-on practical exercises with TensorFlow, focusing on building

and training neural network models. It includes evaluating model performances to understand computational requirements and optimizations and implementing advanced techniques, including transfer learning and hyperparameter tuning. This stage aims to comprehensively understand TensorFlow's capabilities in handling complex machine-learning tasks.

- Third Stage: Scikit-Learn - Following the TensorFlow stage, students began with Scikit-Learn to grasp fundamental AI concepts. This stage covered essential topics, including data preprocessing, feature selection, model evaluation, and implementation of machine learning algorithms.
- Fourth Stage: Keras - After the Scikit-learn stage, Students started with Keras, an advanced Model Implementation and Training, to gain foundational and theoretical experience with the pre-trained models, including VGG16, ResNet101, and DenseNet.
- Fifth Stage: IBM Watson - As the final stage in this stack, this stage introduces IBM Watson to demonstrate the training of AI models in the cloud environments. The students learned about IBM Watson's functions, including visual recognition for analyzing image and video content and machine learning for building and deploying predictive models.

2) Mastering Keras for Project Completion: As a following stage to the AI stack phase, and Building on the knowledge acquired in this phase, this stage aimed to deepen the student's practical understanding of Keras through three key steps. These steps include setting up the Keras environment, exploring different types of machine learning within Keras, and selecting and training the Keras models - see Figure 1 and 2 as examples of the Keras models architectures. The architecture of Team 1's Keras model, is designed for image processing with an input size of 180x180x3. The model utilizes a sequence of layers, including initial preprocessing steps followed by the MobileNetV2 backbone. The final stages involve global average pooling, dropout, and a dense layer that produces a single output, indicating a streamlined, efficient model for image classification. Team 6's Keras model architecture, which handles sequential data with 23 features. The model includes an embedding layer and global max pooling, followed by parallel dense layers that are concatenated. The combined output is further processed by dense layers.

- Environment Setup: Students were tasked with setting up the Keras environment, which included preparing the requirements and downloading the necessary packages and dependencies to ensure that all students could run and test models effectively.
- Learning Types: Students explored different types of machine learning within Keras, supervised and unsupervised learning types. We utilized supervised learning, which includes classification and regression in all three projects.

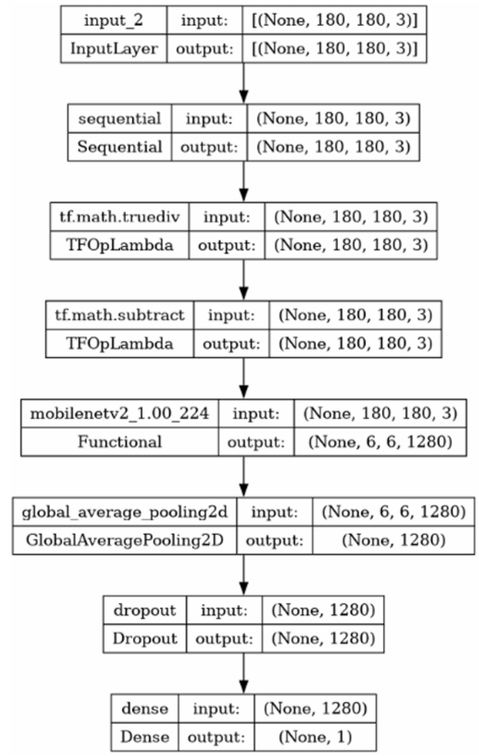

Fig. 1. Team 1 Keras Model Architecture

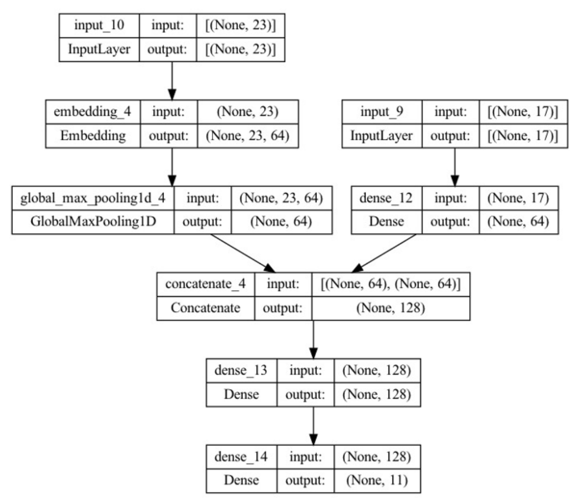

Fig. 2. Team 6 Keras Model Architecture

- Model Training: Students are guided through dataset normalization, preprocessing, running, and training neural network models in Keras, including Sequential and Functional API models, to classify simple datasets to enhance their understanding of model architectures and customize them if needed. They worked on three different dataset types to highlight how different datasets affect model training and performance. see Figure 3.

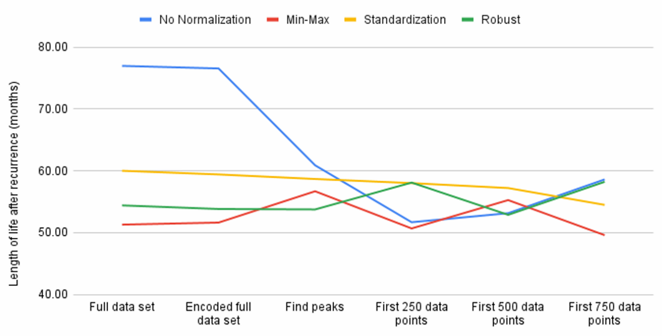

Fig. 3. Team 3: Normalization step: The figure illustrates the impact of different normalization techniques (No Normalization, Min-Max, Standardization, and Robust Scaling) on the length of the 10-year recurrence (months) across various stages of data processing for a breast cancer project.

3) Advanced Model Training Techniques: Following the Keras phase, this stage is designed to help the student customize model architecture and integrate multiple models, handling large-scale datasets and adding more layers if needed. In addition to leveraging transfer learning for better performance and accuracy.

- Black Box Retraining:
  - Focus on the importance of data input and output in retraining models, the relationship between the input and the output, and the role of the loss function in mapping the model input to the output.
  - Exploration of encoding methods, including one-hot encoding, to improve model input handling
- White Box Training:
  - Detailed examination of model layers to understand their functions and interactions.
  - Practical exercises on modifying and adding layers to existing models to see the effects on performance and learning capability.

B. *Medical Foundation stack phase*

The second phase of our approach is designed to detail the process of data acquisition for all three projects and bridge the gap between the AI stack and the medical foundation stack by addressing the integration challenges between these two stacks and finishing the healthcare projects. This phase includes three stages.

1) Problem Domain and Data Acquisition stage: Bridge the gap between the AI stack and the medical foundation stack faces significant challenges, including medical data acquisition, data accessibility and the disconnect between these two stacks. Our solutions to these challenges are as follows:

- Data Acquisition: We collaborated with healthcare providers in the US for the Allergy project and in the UK for the pathology project to obtain de-identified data compliant with legal and ethical standards.
- Data Accessibility: Strict regulations and HIPAA complicate access to medical data, which is essential for training robust AI models. To address this, we ensured that all students signed NDAs before accessing medical data. Additionally,
- Disconnect between Domains: AI professionals and medical practitioners have a notable gap in understanding and expertise. AI experts often lack essential medical training, while medical professionals are unaware of AI's capabilities and limitations. To bridge this gap, we consulted research doctors to explain the medical data and held meetings to discuss and follow up on the project's progress and technical details.

2) Preprocessing and Training: This stage focuses on dataset handling, preprocessing, and finding the appropriate AI models. Each project handled different medical datasets, which required specific preprocessing steps to ensure accuracy and usability for AI modeling.

I) Skin Cancer Prediction Project:

- *Data Description*: This project utilized the ISIC dataset, which contains high-resolution images of skin cancer.
- *Preprocessing Step*: This step included Image normalization and resizing, and techniques were applied to improve model robustness. These included two steps: normalization and resizing:
  - Normalization:
    - Min-Max Scaling: Scaling pixel values to a range of [0, 1].
    - Z-score Normalization: Standardizing pixel values with a mean of 0 and a standard deviation of 1.
  - Resizing:
    - Uniform Resizing: Resizing all images to a fixed dimension (224x224 pixels).
    - Aspect Ratio Preservation: Resizing while maintaining the original aspect ratio, followed by padding.

II) Accurate Cancer Prediction Using Pathology Data:

- *Data Collection Tools*: Fourier Transform Infrared Spectroscopy (FTIR) was used to extract spectral data from encoded cell samples of pathology slides.
- *Data Description*: The project analyzed spectral data from cancer patients' blood serum samples. The dataset included long-term health metrics paired with the spectral image vectors generated by FTIR.
- *Preprocessing Steps*:
  - Data normalization and enhancement techniques were used to standardize the spectral images,

including Min-Max Scaling and Z-Score Normalization.
  - ∗ Peak signal analysis was employed to identify significant data points within the spectral data.
  - ∗ Feature selection tools, including Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA), were used to identify the most relevant features for model training.
  - ∗ scaling the peaks compared to the neighbors and the rest of the data points, which highlights the differences between the different subjects' data points.

III) Allergy Prediction Project:

- *Data Description*: This project used diverse datasets, including skin data and biological markers (Skin color, Skin Condition), and around 10,000 samples from cosmetics products with their ingredients.
- *Preprocessing Steps*: This step included Data cleaning and normalization, preprocessing to the dataset by removing unnecessary columns from the dataset files, removing the (Not a number) Nan values, empty cells. They used One-hot encoding to convert the categorical data into a numerical format to be more easily processed by the machine learning model.

C. *System Development and Deployment Phase*

The Third phase of the approach is designed to illustrate and finish the development, deployment, and testing process for the healthcare projects through the next five stages.

1) System Architecture Design: Students were tasked with designing and integrating the system architecture that combines the trained models with both the front-end and back-end of the applications, as well as ensuring effective deployment on cloud platforms. In the designing phase, students began with an introduction to basic system architecture principles, focusing on integrating various components into an operational unit. They used Micro-services Architecture- see Figure 4 and Figure 5.

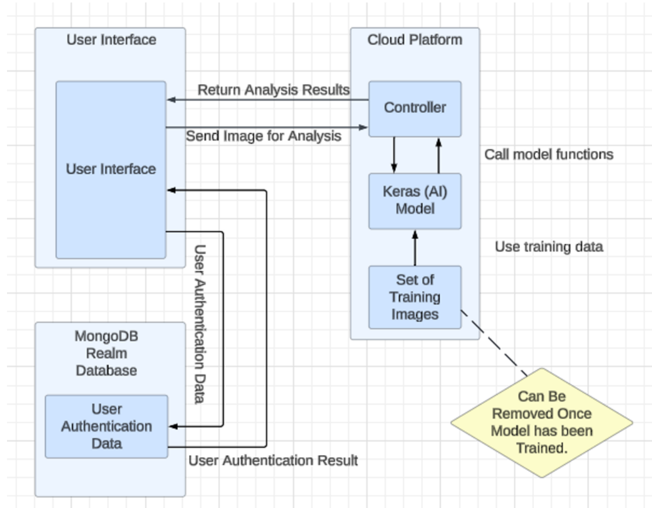

Fig. 4. System Architecture: This figure illustrates the system architecture for a skin cancer project, showing the flow from application front end and authentication through image analysis, leveraging a cloud-based Keras model trained on a set of images.

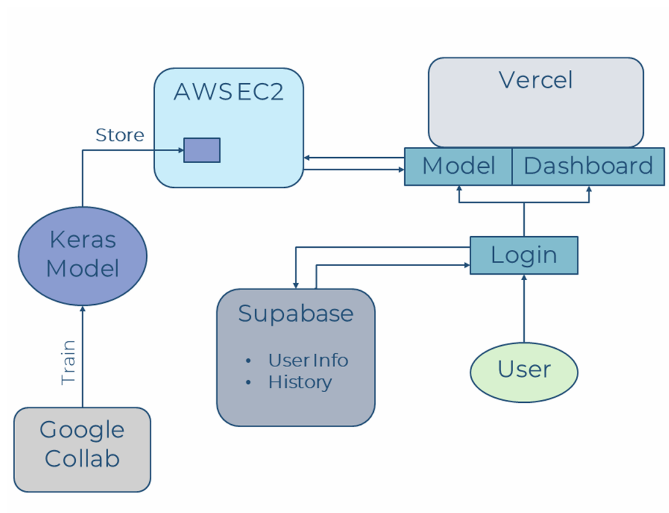

Fig. 5. System Architecture: This figure illustrates the system architecture for a breast cancer project, detailing the integration of AWS EC2, Supabase, and Vercel with a Keras model and user login, supported by Google Colab for model training.

2) System Development:

- Front-end Development: Emphasis was placed on developing intuitive user applications using Flutter for mobile applications and Python for web applications. Figma was utilized to design the UI of the web and mobile applications.
- Backend Integration: Students integrated AI models with backend systems using C (.NET) and Python, employing APIs to facilitate seamless interaction between the front-end applications and the AI models. MySQL was used as the database to support these applications.

3) Integration of AI Models:
Students focused on integrating the trained models with the developed front-end and back-end systems. This phase involved testing with JUnit to validate the operation of AI models within the overall system architecture and Postman for API testing to ensure proper communication between components.

4) System Deployment:

- Choosing Cloud Providers: Students received instruction on selecting appropriate cloud services, including AWS, Azure, and Google Cloud, for deploying their trained

models. Key considerations included cost, scalability, Performance, and geographic availability.
- Deployment Process: Students participated in hands-on meetings to be able to select the required resources (Database resources, Network Resources, security resources), choose the service types, and build, integrate, and configure the components of the system for deploying the process to the cloud platforms.

5) System Operation and Testing: This stage details the process of running the systems and testing their performance after deployment to the cloud platforms, considering the following measures:

- **Go-live Test**: This test focuses on the successful transition of the systems from the development and deployment environments to a live production environment. It includes verifying that all components are correctly configured and ensuring the system is fully functional.
- **System Performance**: This test includes continuous monitoring and analysis of system performance, considering response times, throughput, and resource utilization. Testing tools for this measure include automated monitoring scripts, log analysis, and real-time dashboards to detect performance issues.
- **User Satisfaction**: We assessed user satisfaction by gathering feedback from end users and analyzing their interactions with the system to ensure the systems are user-friendly.
- **AI Models Accuracy**: This test includes an accuracy evaluation of the AI models to ensure that they deliver reliable predictions. This evaluation involves running the models on new, unseen data and comparing the outcomes to known results to determine their precision, recall, and overall performance. We used model performance metrics, including accuracy, Recall, and F1 scores to analyze and identify any need for retraining. We used confusion matrices, and ROC curves to present these scores.
- **Security Status**: This test focuses on the security of the system and its data in handling sensitive information, including patient information. Security measures include implementing encryption and conducting vulnerability assessments to comply with HIPAA regulations.

V. Analysis and Results

This section shows the findings from the six teams' efforts, highlighting key metrics and impacts for all three projects.

A. *Skin Cancer Prediction Project: Teams 1 & 2*

- Accuracy and Performance: Achieved a notable accuracy of 94%, with a sensitivity of 90% in detecting malignant skin lesions. This improvement in diagnostic capabilities could significantly reduce the time for preliminary screenings and provide substantial support to dermatologists, as illustrated in Figure 6 and 7, and 8.
- Technological Advancements: Utilized image processing and AI techniques, including data augmentation, image normalization, and resizing to enhance the model's accuracy.
- Visuals and Supplementary Materials: Provided heatmaps from feature activations within the CNN models and Keras models.
- Scalability and Integration: The trained models were successfully integrated into web-based applications deployed on AWS and GCP cloud environments. The teams compared the models' performance, accuracy, cost, and system load between the two platforms to determine the optimal deployment strategy for real-world applications. The findings for this comparison suggested AWS because of notable differences in cost-efficiency and processing speeds.
- Operation and Testing: Students tested successfully the system functions and their operations within five stages.

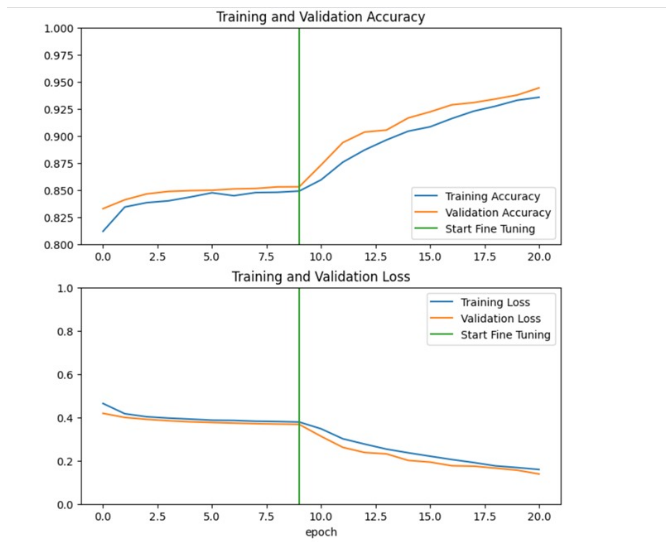

Fig. 6. This figure shows the training and validation accuracy and loss over epochs for Team 1's skin cancer project.

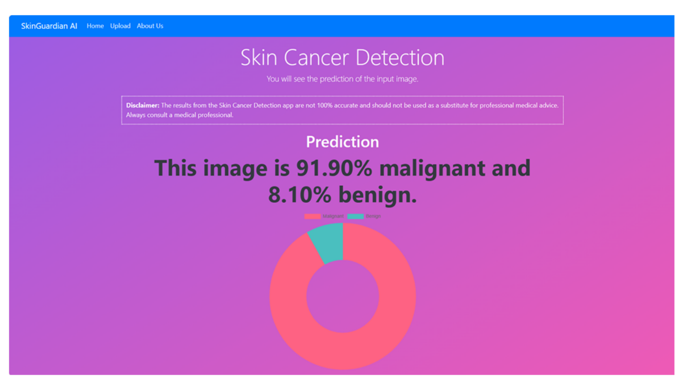

Fig. 7. This figure displays the web application of the skin cancer detection project by Team 1, displaying a prediction where the analyzed image is classified as 91.90 % malignant and 8.10% benign.

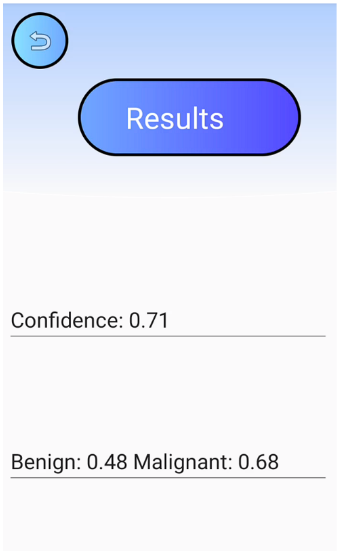

Fig. 8. This figure displays the client application of Team 2's skin cancer detection system, presenting the results with a confidence score of 0.71, and the image classified as 0.48 benign and 0.68 malignant.

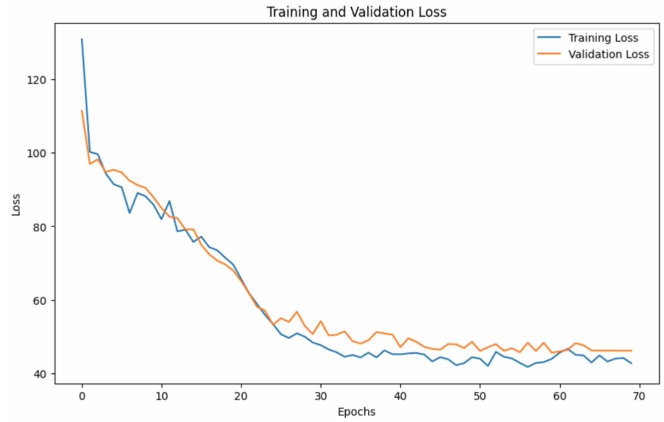

Fig. 9. This figure illustrates the training and validation loss over epochs for Team 3's project, predicting cancer survival after treatment

B. *Cancer Prediction Using Pathology: Data Teams 3 & 4*

- Model Performance: The students leveraged Keras and Random Forest to improve the breast cancer prediction accuracy, including cancer grade, cancer stage, and recurrence, achieving a precision rate of over 85% for the grade, 80% for the stage, and 89% for the recurrence. Significantly outperforming traditional diagnostic methods as shown in Figure 9.
- Innovation in Data Handling: Students utilized data preprocessing techniques, including peak signal analysis and noise reduction to refine the spectral data's quality and enhance the training process.
- Scalability and Integration: The trained models were successfully integrated into web-based applications deployed on AWS and GCP cloud environments. The teams compared the models' performance, accuracy, cost, and system load between the two platforms to determine the optimal deployment strategy for real-world applications. There were notable differences in cost-efficiency and processing speeds, with AWS offering better scalability options for large datasets.

C. *Allergy Prediction Project: Teams 5 & 6*

- Prediction Accuracy: Achieved an accuracy of 88% in predicting allergic reactions, demonstrating the model's reliability in assessing allergy risks. Detailed results and performance metrics are provided in Table I and Table II.
- Client Application: Developed a user-friendly application that streamlined the input and retrieval of patient data. This application significantly enhanced user engagement and facilitated a smoother diagnostic process, making it easier for healthcare professionals to utilize this prediction system.
- Scalability and Integration: The trained models were successfully integrated into web-based applications deployed on AWS and GCP cloud environments. The teams compared the models' performance, accuracy, cost, and system load between the two platforms to determine the optimal deployment strategy for real-world applications. The findings suggested that GCP offers better scalability options for large datasets.
- Adaptation and Feedback: Made continuous adjustments based on initial user feedback to improve the system's predictive accuracy and user interaction.

TABLE I

THIS TABLE COMPARES THE PERFORMANCE METRICS (PRECISION, RECALL, F1-SCORE) OF THE RANDOM FOREST MODEL AND THE NEURAL NETWORK MODEL USED IN THE ALLERGY PROJECT. THE NEURAL NETWORK SIGNIFICANTLY OUTPERFORMS THE RANDOM FOREST MODEL IN RECALL AND F1-SCORE.

Model Type	Precision	Recall	F1-Score
Random Forest	0.20	0.53	0.29
Neural Network	0.35	0.86	0.65

TABLE II

TEAM 6 - THIS TABLE PRESENTS TESTING RESULTS FOR THE RANDOM FOREST MODEL USED IN THE ALLERGY PROJECT, INCLUDING PRECISION, RECALL, F1-SCORE, AND SUPPORT FOR EACH CLASS.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.36	0.52	0.42	664
1	0.28	0.58	0.38	456
2	0.25	0.56	0.34	426
3	0.19	0.54	0.29	328
4	0.14	0.53	0.23	249
5	0.14	0.47	0.22	276
6	0.11	0.44	0.18	225
7	0.15	0.56	0.23	235
8	0.12	0.54	0.20	218
Micro Avg	0.20	0.53	0.29	3077
Macro Avg	0.19	0.53	0.28	3077
Weighted Avg	0.23	0.53	0.31	3077
Samples Avg	0.19	0.40	0.23	3077

VI. Conclusion

This paper detailed an educational approach to bridge the gap between the medical domain stack and the AI stack to make healthcare applications through working on three medical projects (Skin cancer, pathology, Allergy) with six teams of undergraduate senior design students from the Software Engineering Department at Iowa State University. We structured our educational approach into three phases - Fundamentals of AI stack, Medical foundation stack, System Development, and Deployment - We divided Each of these phases into a group of stages.

The Fundamentals of the AI stack phase equipped students with foundational AI knowledge and skills through tools, Including the hardware requirements for setting up the local and cloud environments to run and train the AI models, TensorFlow, Scikit Learn, and Keras. In the second, the Medical Foundation Stack phase, we focused on real-world healthcare projects, where students signed the NDAs before receiving the medical datasets due to the regulations of the data acquisition from the medical professionals; following this step, students started working on the dataset handling, preprocessing, and model selection, and training for all of the three projects. The final phase, the System Development and Deployment, included five stages, starting with designing and developing system architecture components (front-end and back-end), then integrating these components with the trained AI models, and deploying them on cloud platforms, including AWS and GCP. They used comparison tables to evaluate model performance across these cloud providers. We considered system performance, resource cost, model accuracy, stability, and scalability. The last stage in this phase is testing the operations and functions of these systems with some considerations, including the system performance, user experiences, model accuracy, and security status.

In conclusion, our educational approach has successfully demonstrated how integrating AI with healthcare projects can provide valuable learning experiences for undergrad students. By aligning the course and the project objectives with ABET accreditation standards, we ensured that our educational model advanced students' technical skills and prepared them to contribute to the medical industry in the future.

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