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Advanced Dermatology Platform: Deep Learning with VGG19 and DenseNet201, Integrated Chatbot and Community Forum

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Abstract: The present online application employs a contemporary artificial intelligence (AI)-driven solution to transform the process of diagnosing skin disorders. This research uses DenseNet201 and VGG19, two of the most advanced DNN architectures, to build a Convolutional Neural Network (CNN). The enhanced predictive models, built with a dataset of 930 photos divided into ten groups and strengthened by data augmentation, produce remarkably accurate predictions for a range of skin conditions. The website's intelligent chatbot is a standout feature; it was built to answer questions about skin diagnoses, treatment options, and more. This chatbot is designed to help users understand their diagnostic results and find their way on the health journey. In addition, it keeps track of users' prediction histories, so they may learn a lot about their skin's health over time and make educated choices about their medical treatments. In addition, by giving people a place to talk about their struggles and get advice from others, the website fosters a supportive community. The emphasis here is on real human connections, which are great for learning from one another and helping one another out. Firebase facilitates efficient data administration for monitoring forecasts and engaging with the community, while Replit and Voice flow support the CNN model, chatbot, and forum, guaranteeing optimal performance. By integrating cutting-edge AI with a user-centric approach, this web application empowers users with the tools, insights, and support necessary for proactive skin health management.

Introduction

In contrast to the cognitive abilities seen in humans or other living organisms, artificial intelligence (AI) refers to the intelligence demonstrated by machines, which can process information and make decisions in ways that simulate human thought. AI is broadly defined as the study and design of "intelligent agents," encompassing any device, system, or entity that can perceive its environment, analyze data, and take actions that maximize its chances of achieving specific goals. These

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intelligent agents can range from simple automated systems to complex machines capable of understanding and interacting with the world in dynamic, human-like ways.

Due to its wide range of applications, which extend far beyond the automation of routine operations, AI is heavily used by several industries. Machines have the potential to demonstrate intelligence comparable to that of humans in numerous domains, including learning, reasoning, solving problems, and making decisions (Madhuri et al., 2022; Haroon et al., 2024; Swarnalatha et al., 2024; Saraswat et al., 2024; Rao et al., 2024). Many people reach their goals by utilizing advanced academic fields such as ML and DL (Keerthana et al., 2024; Dixit et al., 2024). Here, "machine learning" (ML) means the procedure by which a computer program or other automated system may learn new things without direct human intervention. As a branch of machine learning, deep learning makes use of ANNs to simulate the brain's decision-making process, improving the accuracy of its findings and predictions. The commonly utilized Convolutional Neural Network deep learning model presents a challenge when applied to the diagnosis of skin problems in photos (Nayani et al., 2021). It really shines when it comes to processing and analyzing visual data. Hardware gives an AI system its reasoning and computational capabilities, while software runs the algorithms. Theoretically, algorithms are based on convolutional neural networks, which are essential to AI applications. Pattern recognition, data classification, and prediction are just a few of the many AI tasks that neural networks like Convolutional Neural Networks do.

This research targeted an ML approach for dermatological illnesses based on Convolutional Neural Networks. Because of the intuitive proposed methodology, it should have little trouble being set up online (Rao et al., 2021). This study's primary goal is to help doctors and individuals by increasing the reliability of skin disease diagnostics. With user-supplied data like images and other necessary details, the system may identify if a specific skin condition is present. The computerized diagnostic process is far quicker than the more traditional methods of obtaining preliminary results before visiting a doctor.

The web app predicts skin problems accurately and improves usability. Check earlier projections to follow our skin's growth with this tool. Patients experiencing mood shifts or receiving therapy for long-term skin diseases can benefit from this tool's ability to immediately show designs. A cutting-edge chatbot assistant provides quick support and guidance. This AI chatbot helps patients trust their diagnoses, answer skin health inquiries, and suggest treatments. Using its deep topic knowledge, the chatbot presents accurate and relevant information. A sense of belonging and the value of shared healthcare experiences are promoted on the website's community forum, where users can ask questions and share stories. This builds community by allowing users to learn from each other and offering practical guidance and emotional support.

Using Firebase, the backend to keep secure and always available user information (e.g., their prediction histories or community engagement behavior) The Convolutional Neural Network (CNN) model, the chatbot assistant and community forum all leverage using scalable platforms such as Replit for a seamless user experience with consistent performance. Through a combination of cutting-edge AI technology and human-centric design, our solution redefines access for skin condition diagnosis and provides users with the tools they need to effectively understand their conditions — resources at their fingertips, personal insights available on demand & community in real-time.

Related Work

The authors Saeed Mansour et al. (2023) explore that Skin cancer, caused by uncontrolled DNA mutations, is one of the most common cancers. Early detection greatly improves treatment outcomes, and computer-aided diagnosis using Deep Learning and Machine Learning is rapidly advancing in the medical field. Medical images provide key information for diagnosing skin cancer, and this paper systematically reviews DL methods for early detection, integrating findings through tables and frameworks.

According to Venkatesh et al. (2024), overview of using deep learning models in dermatology. These models have promising accuracy in diagnosis and severity classification among numerous common skin diseases, though they still present limitations in recommending therapy with nuance. Moreover, models face substantial challenges related to prejudice, applicability issues, inconsistent reference standards, and inadequate representation of diversity.

Daneshjou et al. (2022) created the diverse dermatological images dataset to solve important obstacles in dermatological AI. This is the first collection of carefully selected, publicly available skin pictures with a range of skin tones that pathologists have proven. Present AI models need improvement in order to treat a diverse range of skin problems and patient demographics; this dataset reveals their flaws.

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Through fixing the issue of mislabeling skin tones, Groh et al. (2022), a dataset for standardization and transparency in dermatology image collections. This study used a dataset of 460 images to illustrate the execution and implementation of additional identification techniques. Examples of this family are the Individual Typology Angle (ITA-FST) methods, expert comments or even crowdsourcing annotations. In a recent body of work, we show from studies that human-centred methods significantly outperform isolated deep learning at recognizing skin color changes in ways essential to dermatology-related artificial intelligence (AI) technologies.

Benčević examines the impact of skin tone bias on dermatology-related deep learning models, Saeed Mansour et al. (2024). In order to prevent diagnostic errors, preliminary research suggests that training datasets should include a wide range of skin tones. Upcoming research expands upon previous efforts by taking a comprehensive view. Utilizing algorithms that promote equity and enhance data augmentation could be one approach to mitigate the impact of AI biases in cardiac imaging. This study demonstrates that skin lesion segmentation is biased based on skin color; nonetheless, additional research is required to develop more equitable and precise diagnostic tools.

The machine learning and pre-trained deep learning models proposed by Kandhro et al. (2024) aim to improve skin cancer early detection. The VGG19 model was enhanced to accurately predict skin cancer cases through the use of dense layers and max pooling. A total of three more pre-trained models—InceptionV3, DenseNet201, and ResNet152v2—were used to evaluate our results. We used popular machine learning methods like Support Vector Machines (SVMs), K-Nearest Neighbours (KNNs), Decision Trees, and Logistic Regression to extract features from a dataset that included skin lesions that were categorized as benign or malignant. Combining the modified VGG19 model with these classifiers showed that skin cancer diagnosis accuracy was significantly improved.

Groh et al. (2024) explore the possible benefits of deep learning for diagnosing skin illnesses by examining differences in skin tone. Studies have shown that deep learning algorithms frequently generate inaccurate results when applied to several shades of skin. The training data is predominantly to blame for this. This essay hopes to provide fresh approaches to removing these biases by reviewing research on diagnostic accuracy discrepancy. The authors propose that clinical decision support systems incorporate deep learning to enhance the precision of diagnosis.

The deep learning methods used in dermatological research were examined in detail by Jeong et al. (2023). This research aims to analyze current methodologies' pros, cons and challenges. More than one study has looked into the possibility of using deep learning models, such as convolutional neural networks (CNNs), to identify skin cancer and other problems. This paper provides a summary of their findings. Nevertheless, it does recognize important caveats, such as the need for large and diverse datasets, the likelihood of model bias, and the challenge of extrapolating results to other populations.

Jalaboi et al. (2023) developed criteria for evaluating Convolutional Neural Networks ability to explain events in dermatological diagnostics. The current study intends to evaluate the usefulness of current techniques, such as visual heatmaps and feature identification algorithms, in enhancing model comprehensibility in dermatological tasks. The project aims to address the major issues connected with building interpretable models to provide medical practitioners with fresh insights while maintaining diagnostic accuracy. This paper presents a verified approach for analyzing the clarity of Convolutional Neural Networks, which can increase the reliability and usability of biological artificial intelligence (AI) systems designed specifically for dermatology.

Zhang et al. (2019) used a novel strategy to successfully detect skin lesions that integrated convolutional neural networks (CNNs) and attention residual learning. The current study looks at the problem of insufficient feature representation and learning depth, which limit the ability of traditional CNN models to detect skin lesions accurately. According to the authors, attention techniques have the potential to significantly improve residual learning. As a result, the model may focus on critical aspects while reducing the impact of ambient noise. The primary goals of this initiative are to assure the consistency and accuracy of present diagnostic techniques. Additionally, the research investigates the impact of concentrated residual learning on the comprehension and precision of dermatological imaging algorithms.

Jalaboi et al. (2022) developed the complete structure DermX with the aim of enhancing the readability and user-friendliness of automated dermatological diagnosis algorithms. This work aims to optimize the application of deep learning models in clinical settings, expanding on previous endeavors in transparent artificial intelligence and scientific image analysis. After examining several

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methods to model transparency, the scientists developed a comprehensive system that accurately identifies skin irregularities and elucidates the model's decision-making process.

Fukae et al. (2020) endeavoured to utilize Convolutional Neural Networks (CNN) to categorize two-dimensional array images obtained from clinical data. The authors thoroughly evaluate existing techniques for healthcare image categorization, specifically emphasizing the novel application of Convolutional Neural Networks (CNN) in recently created picture formats. The extraordinary potential of Convolutional Neural Networks (CNNs) in improving classification tasks on diverse medical datasets increases diagnostic accuracy and reliability. The application of deep learning techniques to several categories of clinical data is evaluated in this work.

Technology and Libraries

React.js

React is a freely available open-source JavaScript toolkit that is mostly helpful in constructing user interfaces by integrating reusable code components into whole web pages. React is a web framework that was initially created by Facebook and is currently maintained by Meta. Its versatile nature enables developers to use it extensively in isolated components within individual pages or across large websites. React makes it easier to create UI elements that are rendered dynamically using JavaScript by utilizing JSX, a combination of JavaScript and XML. Basically, we just need to understand how to import the libraries and use them in React.js.

Library (react-router-dom)

A routing library that enables navigation and routing within React applications, allowing developers to create single-page applications with multiple views.

Flask

Python has a lightweight web framework called Flask to make building online apps easier. Bypassing pre-installed functionality like an Object Relational Manager (ORM) allows Flask, a microframework, to concentrate on delivering an extensible, simple core. Serving as a WSGI web application framework, it provides necessary features, including URL routing and a template engine. Flask requires Python 2.7 or later to be installed. The main application will remain simple and scalable thanks to the framework. Flask doesn't come with database functionality by default, but you may add it with extensions.

Firebase

Providing a wide variety of tools and services, Firebase is an all-inclusive platform for developing online and mobile applications. After being created by Firebase, Inc., Google bought it out in 2014. With Firebase, it's easy to build sophisticated applications with authentication, cloud storage, analytics, real-time databases, and hosting features. It is applicable to developers on many platforms and is interoperable with multiple languages, including Objective-C, JavaScript, and Java programming. Firebase is already quite flexible and compatible with building applications, but its ability to interact with other Google products makes it much better.

TensorFlow

It has several uses, but its primary concentration is on deep neural network training and inference. Originally released in 2015 under the Apache License 2.0, TensorFlow was developed by the Google Brain team for use in internal research and production. Google unveiled TensorFlow 2.0, an upgraded version, in September 2019. Among the many languages that TensorFlow can communicate with are Python, JavaScript, C++, and Java. CSS styles HTML elements on web pages, controlling their appearances like layout, colors, fonts, and spacing. By using CSS selectors, developers apply styling rules to specific elements, ensuring a consistent and attractive look across different devices. It separates page structure (HTML) from presentation (CSS), making web development easier to manage and update.

Methodology

To provide the corresponding disease from the image, we have to perform a few important steps: accumulating the data, analyzing it, and building it.

Figure 1 shows a system architecture that illustrates a user interaction paradigm where the user initiates the process by either logging in or signing up. Upon successful authentication, the user is presented with three primary options: uploading an image, engaging with other users, or interacting with a chatbot. Each of these pathways provides distinct capabilities and interactions within the system, tailored to meet particular user requirements.

Figure 2 illustrates the overview of the Web Application for Advanced Dermatology by using CNN and DCNN.

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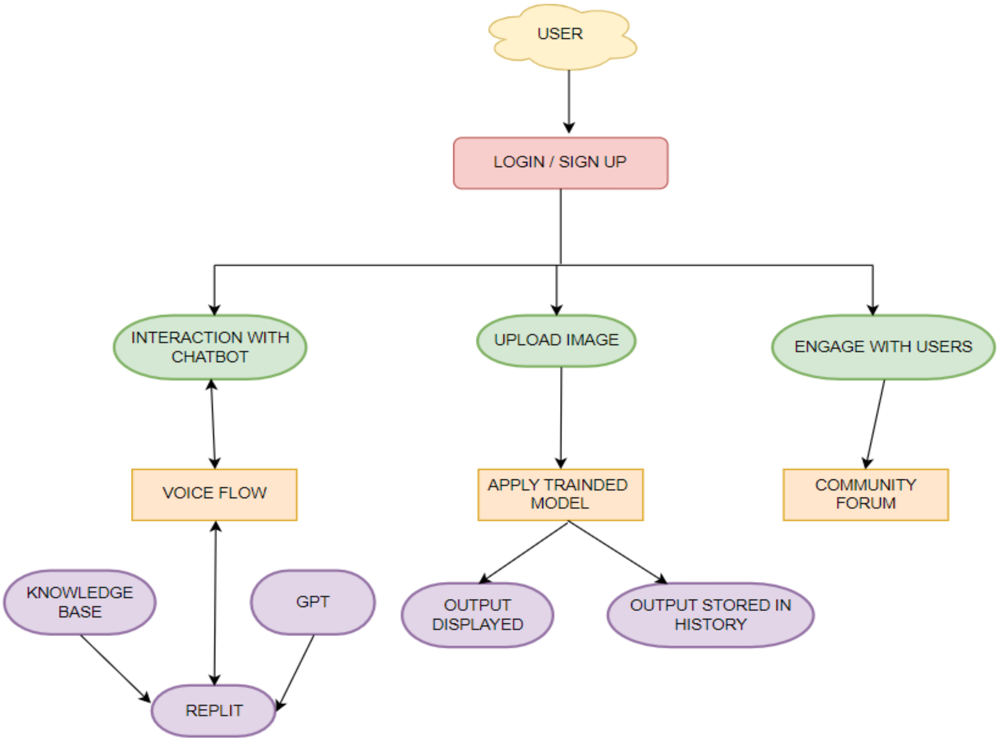

Figure 1. System Architecture.

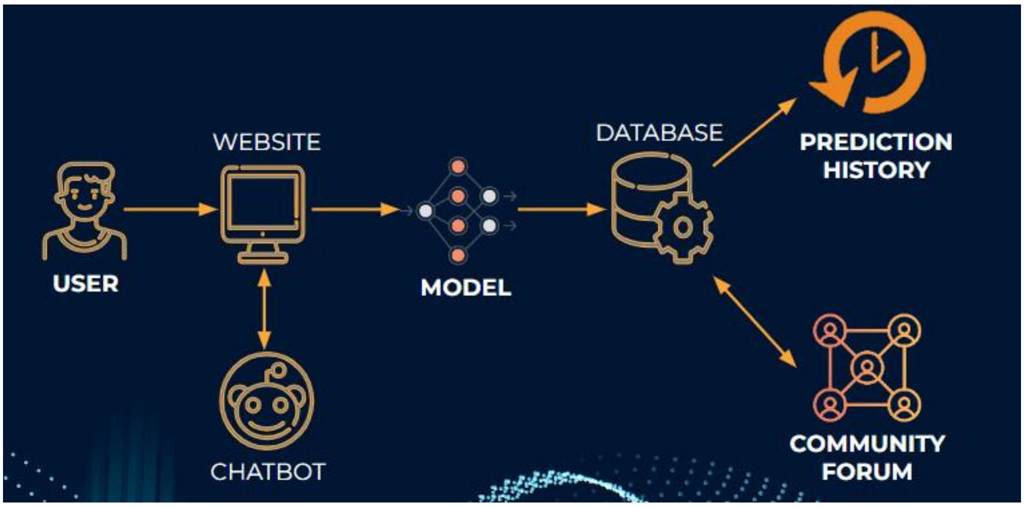

Figure 2. Block diagram of the Application.

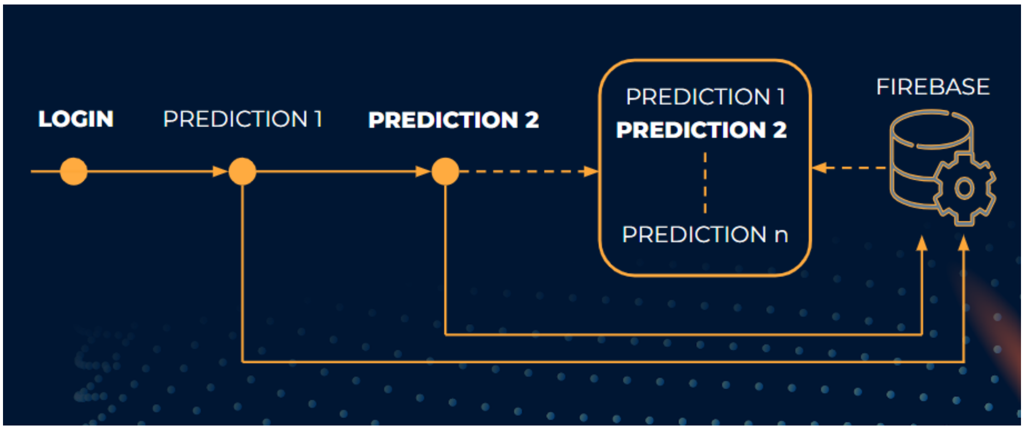

Figure 3. Prediction Workflow with Firebase Integration.

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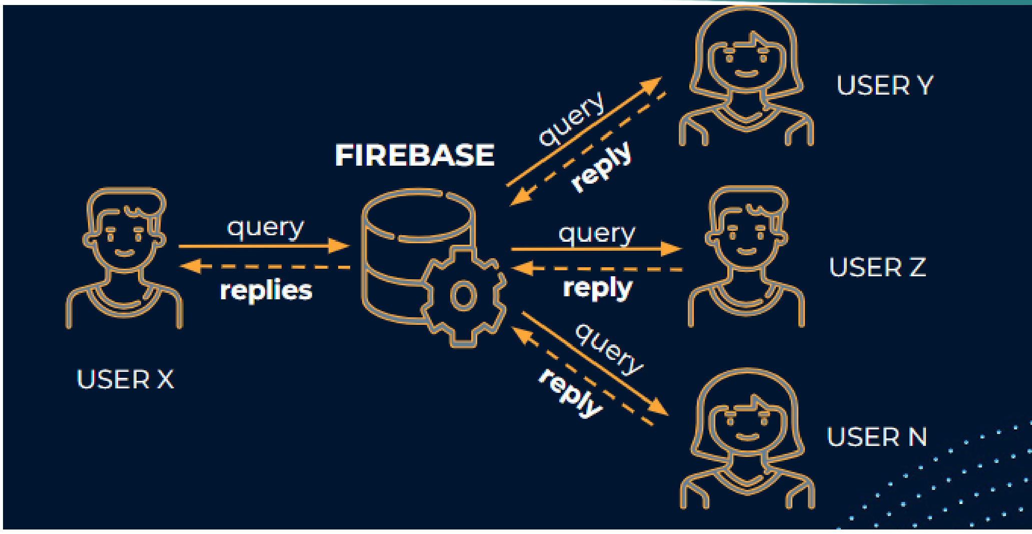

Figure 4. Multi-User Communication Flow with Firebase Integration (Community Forum).

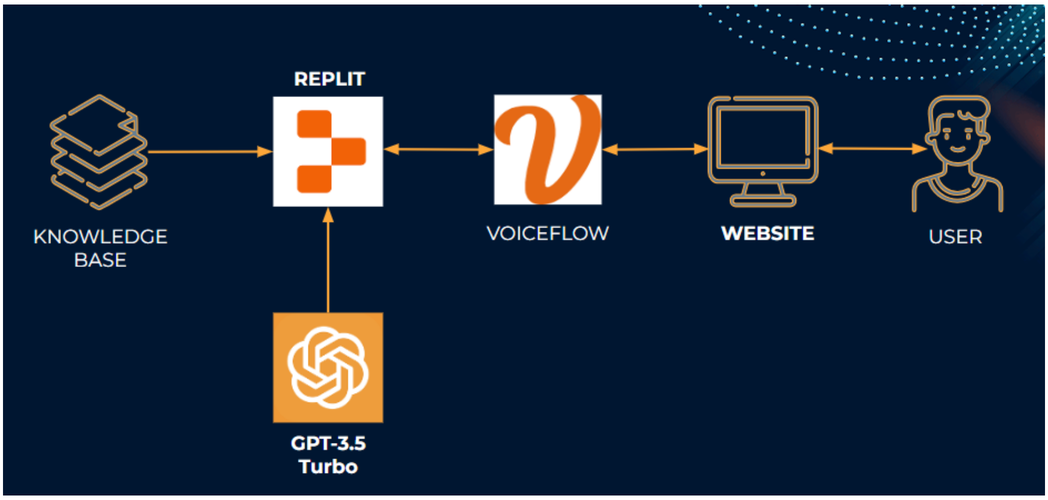

Figure 5. ChatBot - User Interaction Flow with GPT-3.5, Voiceflow and Replit Integration.

The above figure 3 depicts the prediction flow with Firebase integration. After the user chooses to upload an image, the image is processed by a model. The model analyzes the input and provides an output immediately displayed to the user. In addition to this real-time output, the result is stored in the user's history, allowing for future reference or retrieval. This pathway is particularly useful for users who need to work with visual data or use images for further analysis or processing.

Figure 4 shows how to engage with other users through a community forum. This platform facilitates communication, idea sharing, and collaboration among users. The community forum facilitates engagement and cooperation, offering a platform for users to deliberate on diverse subjects, exchange unique perspectives, and solicit guidance from their peers. This pathway highlights the social and cooperative dimension of the system.

The above figure 5 illustrates the engaging process with a chatbot specifically developed to aid users with a range of activities. The chatbot is powered by Voiceflow, a specialized platform optimized for generating conversational conversations. Behind the scenes, Replit creates a connection with the chatbot to execute code or retrieve relevant data. In order to provide more complex or customized interactions, the conversational agent uses the GPT model to generate replies in natural language. Moreover, a knowledge base provides existing information, allowing the chatbot to answer customer queries promptly. This pipeline highlights the system's ability to deliver a dynamic and captivating experience propelled by artificial intelligence for consumers.

In general, the model provides a versatile interaction framework that enables users to participate in several ways according to their requirements, such as image processing, interactive community engagement, or talks driven by artificial intelligence.

Dataset Description

The study collected a dataset of 932 photos, categorized into 10 distinct groups, including nevus, acne, candidiasis, urticaria hives, lupus, eczema, and bullous. Each category comprises 100 images: warts molluscum with 97 images, impetigo with 72 images, and acanthosis nigricans with 63 images.

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Figure 6. Reference Dataset (Acne).

Figure 7. Reference Dataset (Lupus).

Figure 8. Reference Dataset (Bullous).

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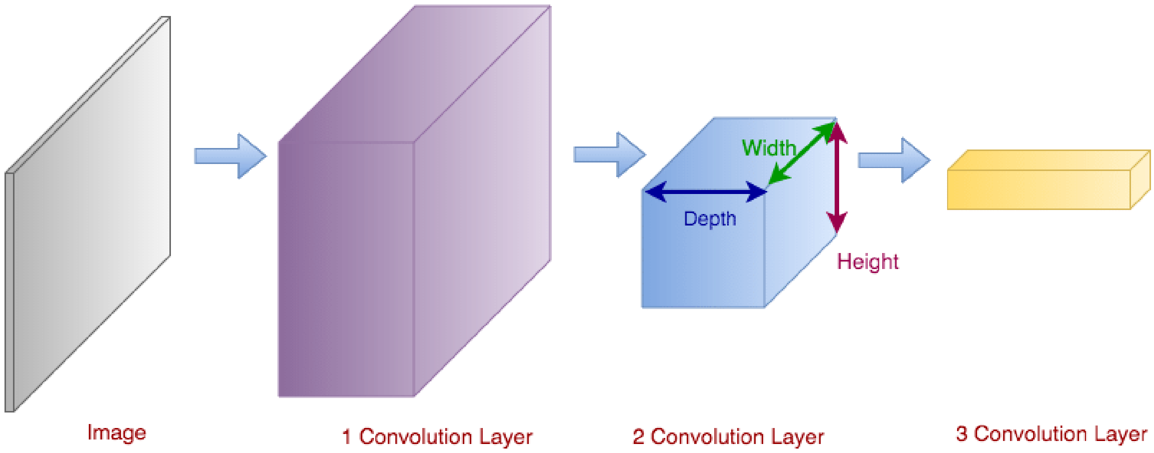

Figure 9. The layers of a CNN have neurons arranged in 3 dimensions: width, height and depth.

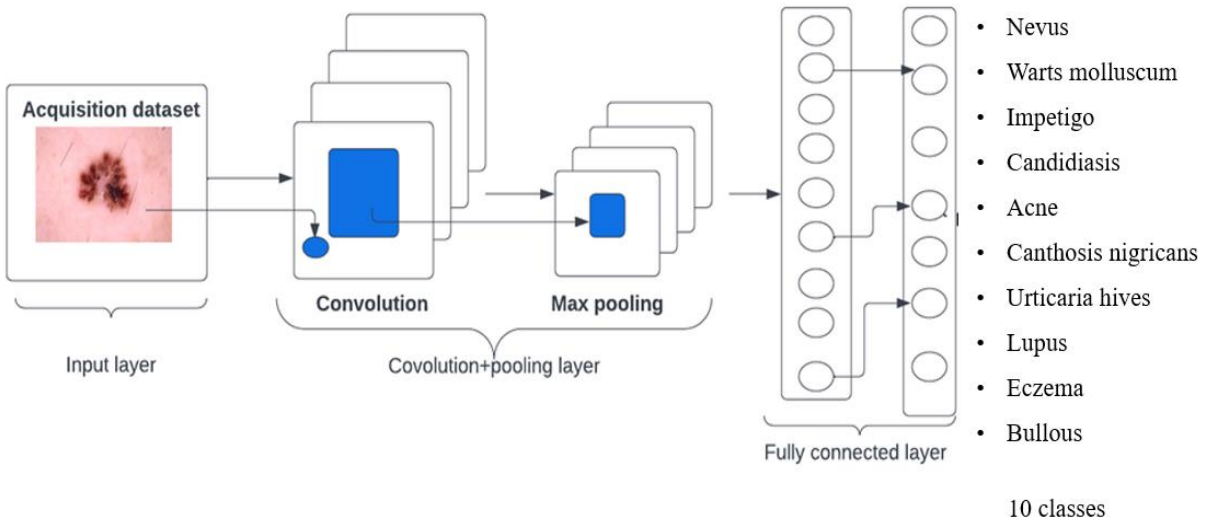

Figure 10. High-level overview of CNN architecture.

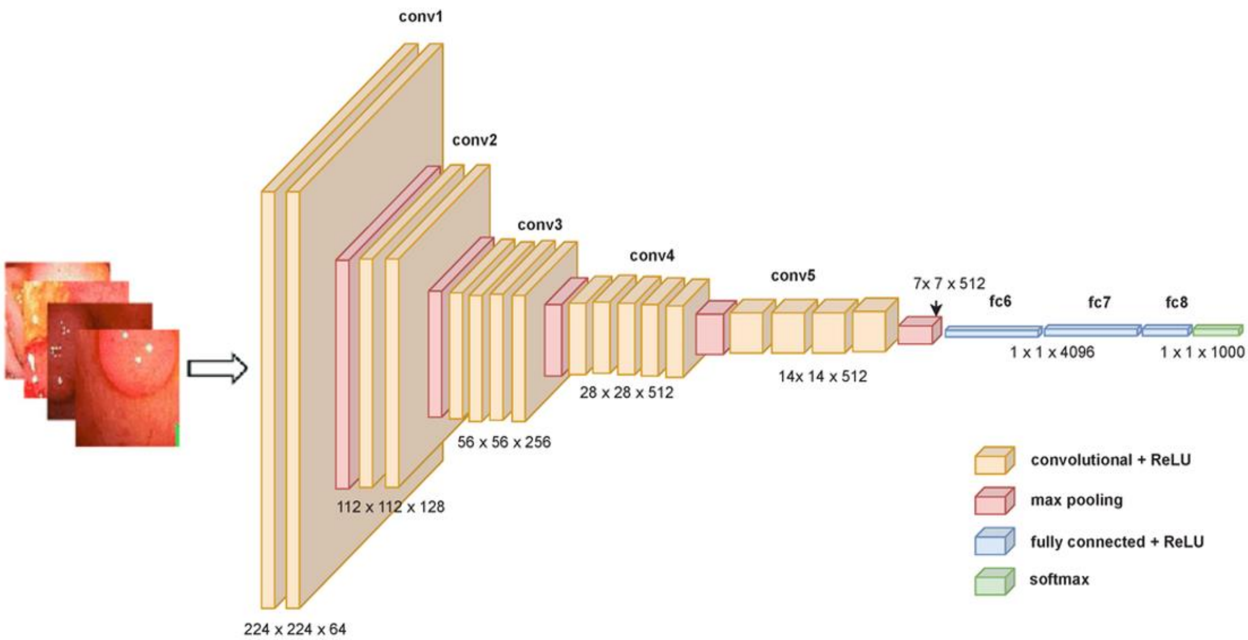

Figure 11. Architecture of the well-known CNN model VGG19.

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Database Integration

For efficient data management, we utilised Firebase to fulfil several needs within the application. We utilized the Firebase Realtime Database to securely store essential user data, such as usernames and user IDs, and facilitate community engagements through message storage and retrieval. Using Firebase Storage, we implemented scalable and secure storage solutions to effectively manage user-uploaded photos. The integration facilitated the maintenance of a robust and well organized data management system for our application.

A convolutional layer network that performs convolutional operations using dot products makes up the hidden layers. After these convolutional layers, activation functions such as Rectified Linear Unit (ReLU) are typically applied. Pooling, completely connected, and normalizing layers are some possible extra network layers. The components are referred to as "hidden" because their internal activities and modifications are crucial to the network's performance and operation but are not easily visible (Jeong et al., 2023; Jalaboi et al., 2023; Fukae et al., 2020).

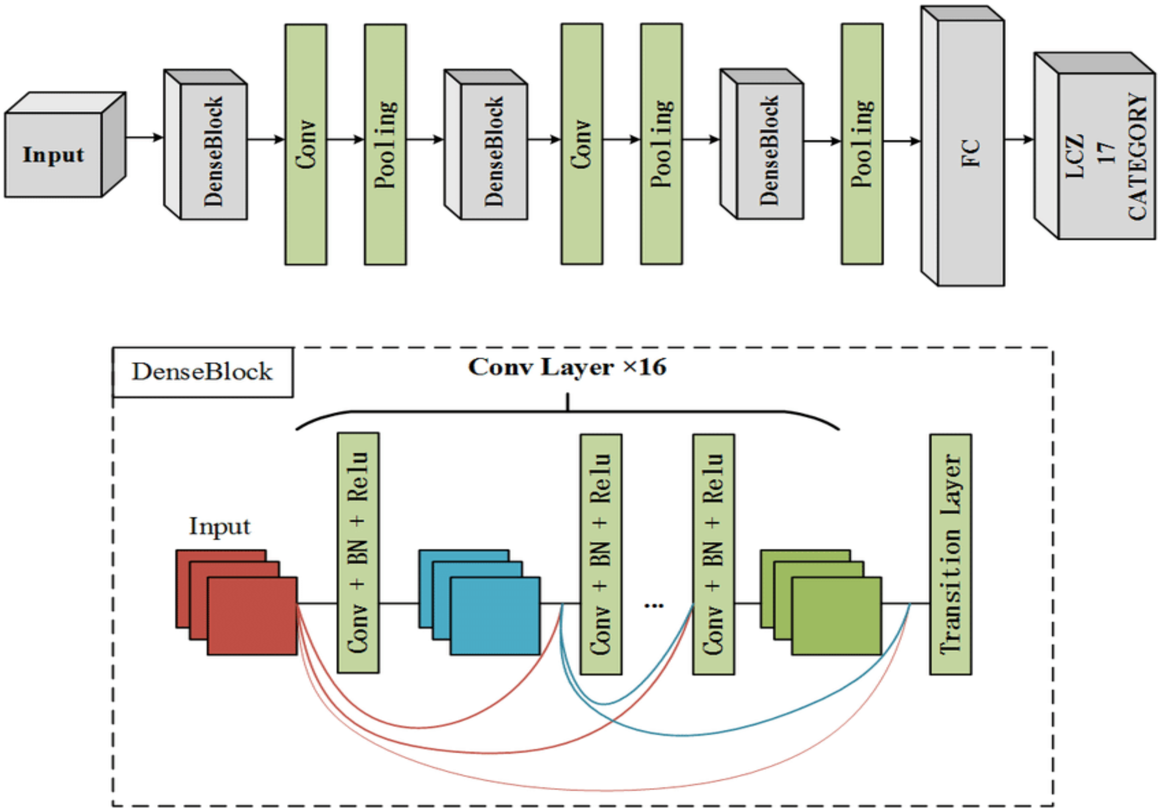

Figure 12. Design of the DenseNet201CNN Model.

Chatbot development with Voiceflow

The Replit IDE and the GPT-3.5 Turbo model laid the chat tool's foundation. Because it was trained using a knowledge base that is specific to five distinct fields, this model is assured to produce accurate and relevant results. To control the conversation's tempo and build user interactions, we turned to Voice flow.

Algorithm used

Convolutional Neural Networks

Convolutional neural networks (CNNs) are the fundamental units of neural networks that can recognize faces, classify objects, and detect and identify objects. The image resolution determines the input data dimensions (height h, width w, and depth d) of the pixel arrays used by CNNs. CNN architecture has multiple hidden layers in addition to an input and an output layer.

Pre-trained DCNN architectures

(i) VGG 19 Architecture:

The VGG19 architecture is a comprehensive convolutional neural network developed by the Visual Geometry Group, which is affiliated with the University of Oxford. The present model is an extension of the VGG16 model, distinguished by its inherent simplicity and comprehensive coverage. The VGG19 architecture consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. VGG19 employs three fully connected layers downstream of the convolutional and pooling layers, specifically designed for classification applications. The simplicity and consistency of this design make it particularly effective in image classification and feature extraction applications (Kandhro et al., 2024).

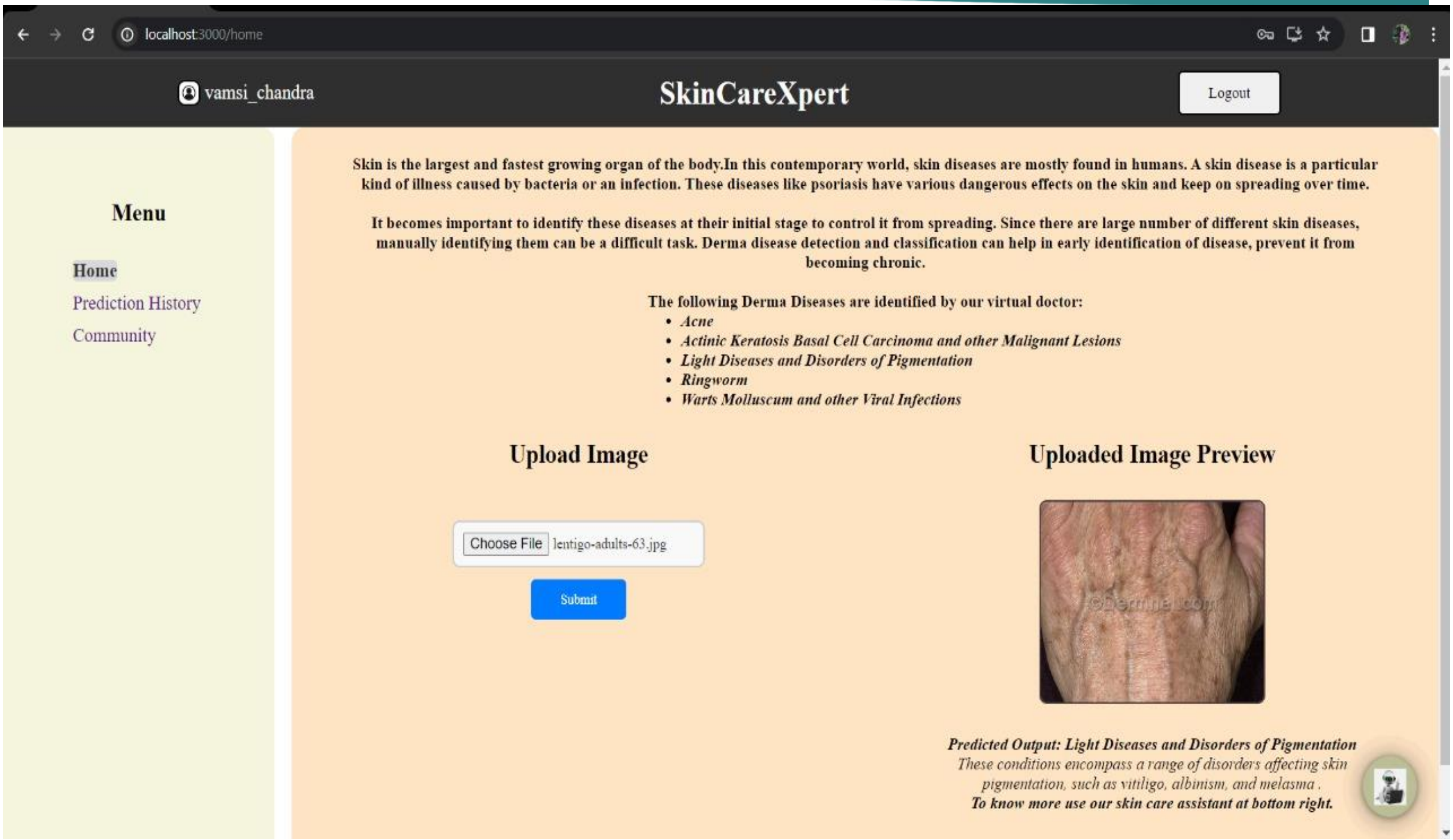

Figure 13. Home Page of Application.

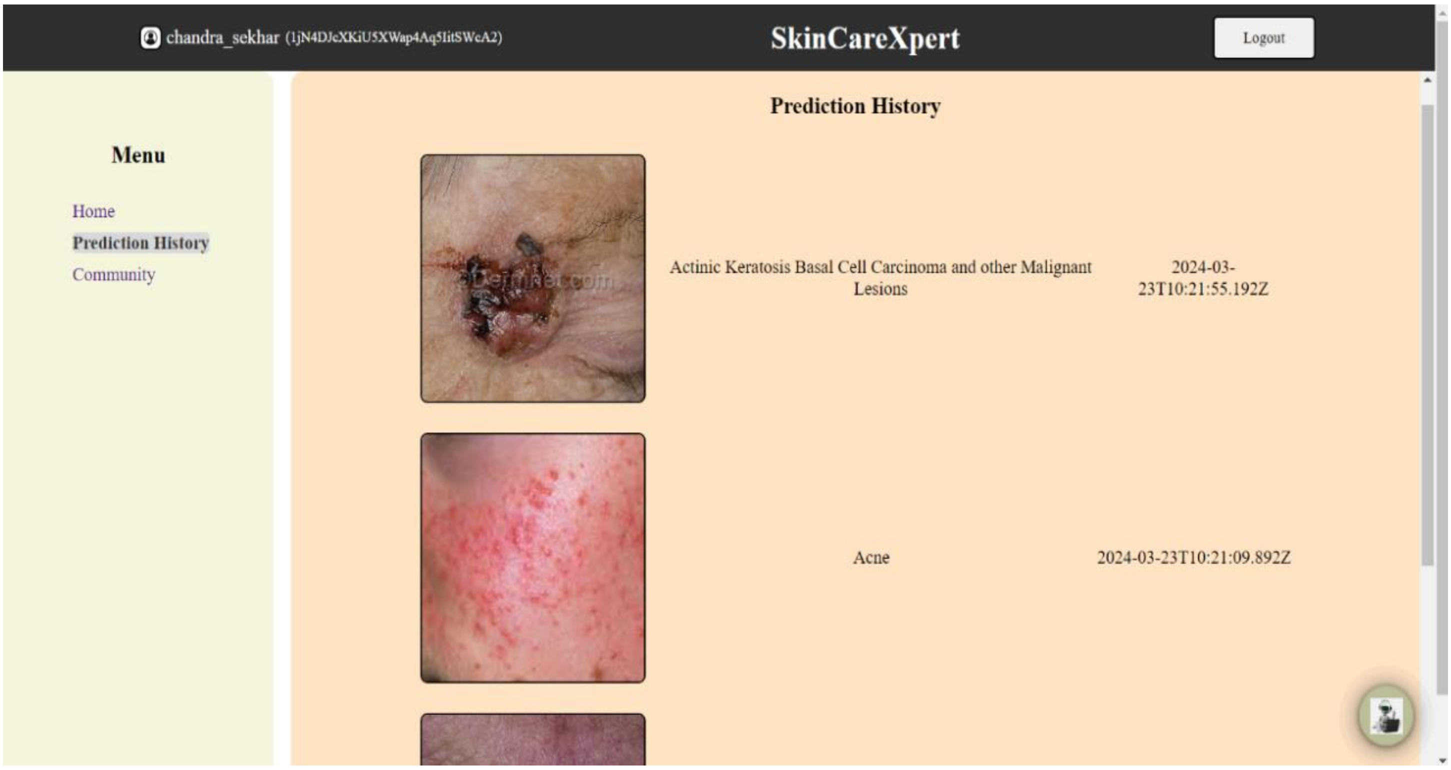

Figure 14. Prediction History Page.

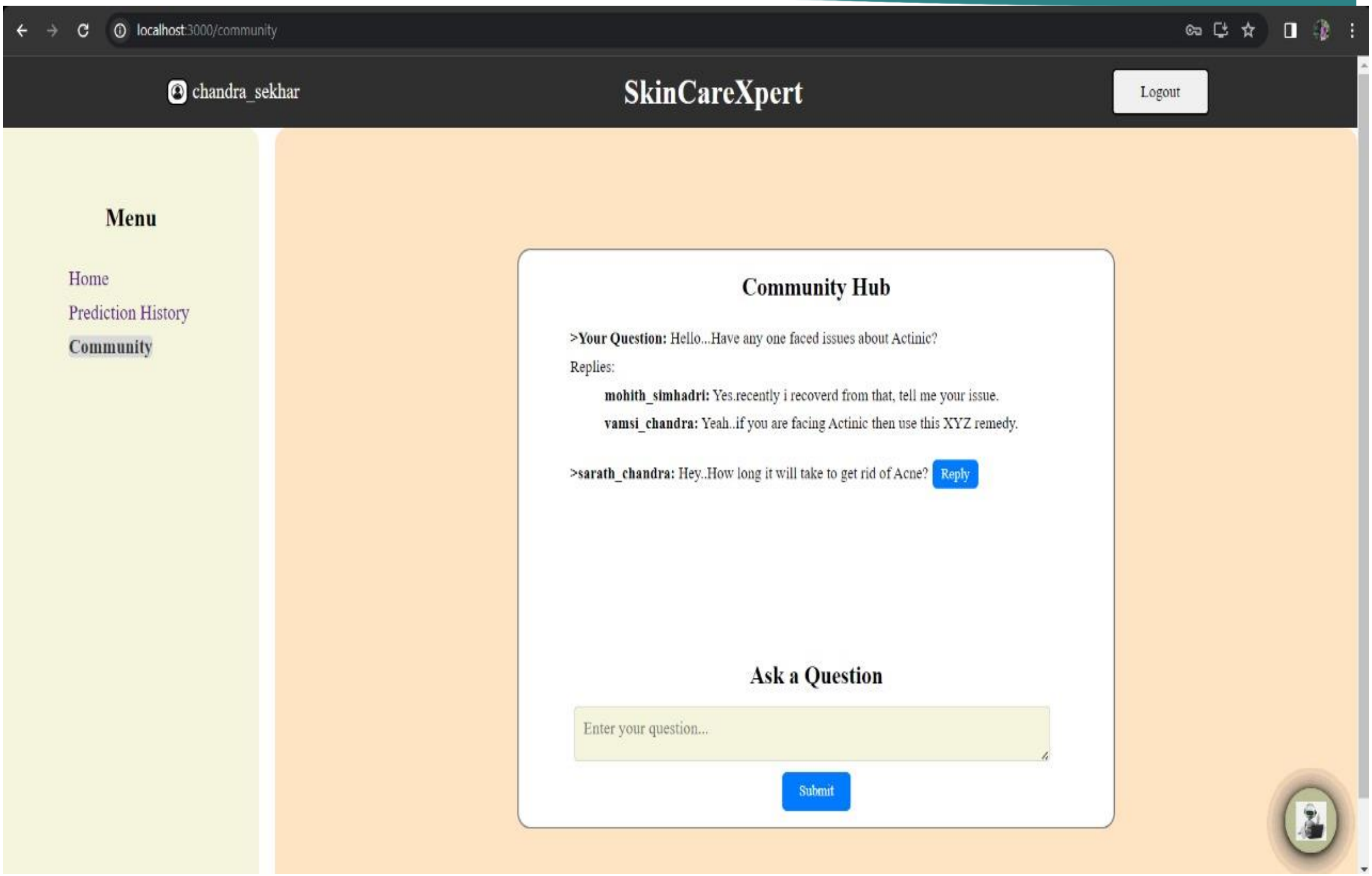

Figure 15. Community Page.

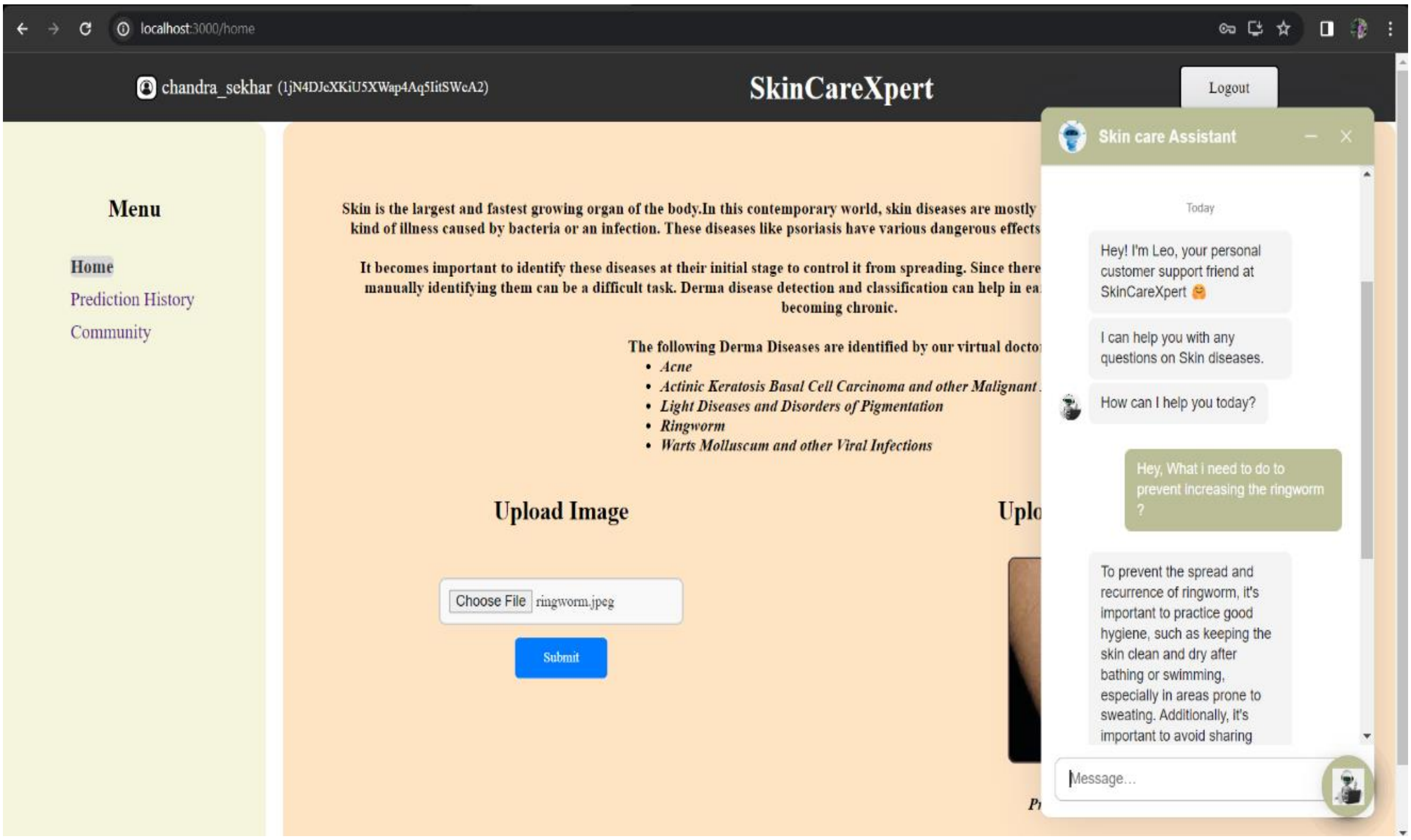

Figure 16. Virtual Assistant.

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(ii) DenseNet 201 Architectural Design:

The deep convolutional neural network DenseNet201 is a member of the DenseNet family and is distinguished by its exceptionally dense connection structure. DenseNet201, developed by the Cornell University team, enhanced network performance by incorporating dense blocks, where all inputs from preceding layers are transmitted to each subsequent layer. Layers of dense blocks linked by transition layers make up DenseNet201's 201-layer architecture. The feed-forward connections between each layer and every other layer in these dense blocks allow for feature reuse and reduced parameters. With this layout, we can optimize data flow, facilitate effective training, and put an end to the disappearing gradient problem. DenseNet201's robust feature learning capabilities make it a top performer in picture categorization tasks (Kandhro et al., 2024).

Results and Discussions

Testing: We tested our application with sample images and produced the results according to the given image.

Figure 13 describes the home page of our website, which provides a brief description about our application, a list of diseases that our model predicts and an input file upload option and we see that we have uploaded an image and given the corresponding prediction. Figure 14 specifies the history of images that he predicted. So, that every user can make their own predictions, internally, these images are stored in Firebase and fetched when this page is rendered.

The Figure 15 shows how the community forum works. If the user asks a question, then any of the other users can reply to the question, and the reply answer can be viewed here. And we can also reply to the other users' queries.

Figure 16 shows how the chatbot works. Here, we asked a query regarding ringworm and the chatbot itself came up with the answer, which is in our knowledge base. It internally sends the query to voice flow, takes it to GPT, and sends this reply to voice flow.

Conclusion

When patients cannot see a doctor right away, our research on skin disease prediction technology can give them rapid health information. Users can upload images to identify possible skin issues, which are then classified into different types of diseases so they may take the necessary precautions. Acquiring enough picture data to train deep-learning models was our main obstacle. But, we still managed to build a CNN model utilizing pre-trained architectures such as DenseNet201 and VGG19. The system's community forum, chatbot support, and prediction history all work together to make the user experience better and foster collaboration.

Conflict of interest

None

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