HIGH SCHOOL EDITION
Journal of Student Research

Developing and Testing Deep Learning Models for Monkeypox and Herpes Zoster Rash Differentiation

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ABSTRACT

Monkeypox (mpox) is a viral infection known for its pimple-like skin rashes found across the body. Since the 2022 outbreak, monkeypox has been mistaken for similar conditions, such as herpes zoster (shingles). In the past, deep learning, a form of machine learning in which software models learn to form conclusions using artificial neural networks (ANNs) similar to that of the human brain, have been utilized to identify various dermatological conditions. Utilizing the engineering method, the following research question was inquired: How can deep learning be applied to a mobile application to distinguish monkeypox viral lesions from herpes zoster viral lesions? ResNet50 and MobileNetV3, two deep-learning models, were trained utilizing transfer learning for the task of differentiating between monkeypox and shingles. ResNet50 and MobileNetV3 were then tested utilizing a separate testing set of images. Both models achieved an accuracy of 93.10 percent, with ResNet50 achieving a loss of 17.03 percent and MobileNetV3 achieving a loss of 29.30 percent. It was concluded that ResNet50 may be more precise due to its lower loss percentage, indicating fewer instances of errors. An end-user prototype of a mobile application was created to simulate these deep-learning models. These findings suggest that deep learning is an efficient and precise solution to prevent the misdiagnosis of monkeypox, potentially hindering the rising cases of this virus while aiding in proactive measures to identify and treat monkeypox victims.

Introduction

In 2022, the monkeypox virus took the scene on a global scale, earning its name as a national health emergency in the United States and spreading to over one hundred countries that had not recorded the virus prior to 2022 ("Mpox in the U.S.", 2023). Monkeypox (mpox) is a zoonotic virus, a virus transferred from animals to humans (World Health Organization [WHO], 2022). Similar to smallpox but less severe in symptoms, monkeypox has originally been identified in the central and western regions of Africa (WHO, 2022). Since its identification in humans in 1970, monkeypox has spread to neighboring countries with its first outbreak outside of Africa being in the U.S. in 2003 (WHO, 2022). This sparked the spread of monkeypox to other countries, such as Singapore, Israel, and the United Kingdom, over the years (WHO, 2022). However, in 2022, monkeypox cases began to be identified rapidly in non-endemic countries, raising concern in the medical community (WHO, 2022).

Monkeypox Symptoms and Implications

Monkeypox symptoms are usually mild among most victims; however, various symptoms are common, such as swelling of the lymph nodes, abdominal pain, muscle ache, sweats, back pain, fever, respiratory issues, and headache (Bryer et al., 2022). One of the most evident signs of the virus is its skin lesions. Typically after one to five days of contracting a fever, skin lesions begin to appear, which are usually first found around the mouth, anus, and genitals before spreading to the face and limbs of the body (Bryer et al., 2022). Once the rashes have scabbed over and a new layer of skin has appeared over them, which is usually two to four weeks after the appearance of the first skin lesion, an individual is considered to be no longer infectious.

The recent monkeypox outbreak has led to numerous impacts regarding discrimination, detriments to the healthcare system, and the spread of misinformation. The current monkeypox outbreak has strained healthcare systems in the United States and worldwide. In the US, vaccine shortages and booked appointments leave those in need neglected and vulnerable to infection (Ollove, 2022). In Africa, rebounding from the coronavirus (COVID-19) pandemic while battling monkeypox has been a struggle, as healthcare professionals are not easily accessible due to COVID-19, isolation spaces have been exacerbated, and the general public has a lack of information regarding the virus, especially in rural areas (Uwishema et al., 2022). Furthermore, networks of misinformation have been detrimental to monkeypox victims who utilize this inaccurate information. In fact, in a recent study performed by Dr. Yeimer Ortiz-Martínez, internal medicine Chief Resident at the Industrial University of Santander, invalid information regarding monkeypox was prominent on the social media platform, Twitter, raising concern for potential users following incorrect advice (Ortiz-Martínez et al., 2022). This trend is also standard on other social media platforms, including Facebook (Ennab et al., 2022).

Herpes Zoster and Epidemiology

Herpes zoster, more commonly known as shingles, is a viral condition that involves the reemergence of the varicella-zoster virus, which also causes chickenpox (Nair and Patel, 2022). When the dormant varicella-zoster virus reactivates in the immune system, typically in the elderly or adults, victims experience a rash, usually around the abdomen as well as the face, limbs, feet, and neck (Nair and Patel, 2022).

This long-standing virus is common in the United States. It is estimated that over one million people in the U.S. experience shingles annually (“Shingles (Herpes Zoster)”, 2022). Though the Varicella Vaccine can prevent both chickenpox and shingles effectively, herpes zoster is still increasingly common in the United States, especially in the young adult population (“Shingles (Herpes Zoster)”, 2022). Globally, herpes zoster has been predominant in countries on nearly every continent, including the United Kingdom, Germany, Canada, Taiwan, and South Korea (Yawn and Gilden, 2013). Despite vaccinations, these countries have recently experienced gradual increases in herpes zoster cases, causing unease in the medical community (Yawn and Gilden, 2013).

Similarities Between Mpox and Herpes Zoster

There have been growing concerns regarding the misdiagnosis of monkeypox for other skin infections. According to Centers for Disease Control and Prevention (CDC) Director Rochelle Walensky, it is common for monkeypox to be mistaken for similar skin conditions or a sexually transmitted infection (Soucheray, 2022). Research led by Azhar Hussain, affiliated with Touro College of Pharmacy, discovered that monkeypox is known to look like scabies, syphilis, herpes zoster, measles, and other skin infections (Hussain et al., 2022). He emphasizes that correctly diagnosing an individual’s condition would lead to healthcare providers correctly treating their patients, ultimately targeting rising monkeypox cases (Hussain et al., 2022). With constant misinformation online and a lack of general knowledge between herpes zoster and mpox, these conditions could be easily confused with each other, leading to unresolved cases or incorrect treatment both at home and in clinical settings. The utilization of technology could combat confusion between these two skin conditions through the involvement of Mobile health.

Mobile Health

Mobile health (mHealth) is commonly used as a general term for technologies that aid in health practices in the medical or public health fields that are supported by mobile devices (Park et al., 2016). Mobile applications have increasingly become prominent in the medical community, serving as cost-effective means of medical knowledge (Lee et al., 2018). Studies show that managing symptoms can be aided through the use of such mobile applications (Lee et al., 2018). Mobile health has been shown to be extremely beneficial in promoting healthy habits through a broad range of treatments from encouraging improved mental health in veterans to monitoring chronic diseases, such as in the field of gastroenterology (Kernebeck et al., 2020; Owen et al., 2015).

Mobile health practices have also been integrated into the field of dermatology. Regarding diagnosis from patient images, mHealth applications have been proven an effective means to diagnose skin conditions related to skin cancer, oftentimes being more accurate than dermatologist diagnoses (Haggenmüller et al., 2021; Chuchu et al., 2018). Cosmetic skin conditions, such as acne, have also been shown to be accurately classified into specific categories reflective of dermatologist-level diagnosis (Ker et al., 2018; Huynh et al., 2022).

Benefits of Mobile Health

In addition to their accuracy, mHealth applications can provide an accessible means of medical treatment or monitoring. For instance, in a 2018 periphery study led by Liesbeth F. Mieras, a doctor and a technical consultant at the Netherlands Leprosy Relief in Amsterdam, health workers in Mozambique were able to better diagnose their patients with neglected tropical diseases early on utilizing a mobile application. Furthermore, with teledermatology saving "costs associated with travel and workplace absenteeism", mHealth applications serve as accessible healthcare aids (Ouellette and Rao et al., 2022).

Mobile health has also been proven beneficial in the management of symptoms related to viral infections. For instance, "malaria and cholera outbreaks" in Haiti and countries of West Africa were managed using mHealth features to aid in "containment strategies" and "relief assistance" for victims (Dahiya and Kakkar, 2016). More recently during the coronavirus (COVID-19) pandemic, novel mHealth systems helped victims monitor and better understand their symptoms (Raposo et al., 2021). For example, mHealth tools worked directly with the government to track COVID-19, such as in India (Sharma et al., 2022).

Deep Learning and Transfer Learning

Mobile health applications typically rely on advanced software programming through artificial intelligence. One such programming technique is deep learning, generally defined as programming that relies on artificial neural networks (ANNs) consisting of numerous layers of code to achieve deep analysis of data to create accurate predictions (Meijering, 2020). Deep learning is a form of machine learning, which is the development of software models to mimic the human thought process (Meijering, 2020). In image data, neural networks known as convolutional neural networks (CNNs) are commonly used and have been increasingly explored to solve medical identification problems (Meijering, 2020). The practice of transfer learning, utilizing previously made deep learning models for one purpose to fine-tune in order to target another problem, has become a topic of discovery in the medical community, especially in regard to dermatology (Ayana et al., 2021).

Previous Findings

As of late, two research studies have been published testing the concept of mobile applications and monkeypox identification. In a study published in July of 2022 led by Shams Nafisa Ali, a biomedical engineer and lecturer in the biomedical engineering department at Bangladesh University of Engineering and Technology, researchers tested the feasibility of deep learning to identify monkeypox amongst its commonly confused relatives: smallpox and measles (Ali et al., 2022). After developing three main deep-learning models based on a collection of skin lesion images from public databases and websites, the best model with an accuracy of 82.96% was chosen to develop a prototype mobile application (Ali et al., 2022). Ali and her team believe that with more research, this model could be applied to quickly identify the early stages of monkeypox (Ali et al., 2022).

Published in October of 2022, another study utilizing a deep learning model to classify monkeypox skin lesions was designed and tested in a peer-reviewed study led by Dr. Veysel Harun Sahin, a lecturer in the Software Engineering Department of Sakarya University (Sahin et al., 2022). Utilizing a public dataset of monkeypox skin lesion images, a formulated, pre-trained deep network was integrated into a mobile application through transfer learning (Sahin et al., 2022). After testing the application on three different devices, Sahin and his team found that the application was able to classify a skin lesion as positive or negative for monkeypox with 91.11% accuracy (Sahin et al., 2022). Researchers foresee that this deep network could be trained for other skin conditions and directly used to diagnose skin conditions like monkeypox (Sahin et al., 2022).

Gap in Research

Though the studies described above do analyze monkeypox identification, it is important to note that these investigations developed mobile applications that identified skin lesions as either mpox or "other", with "other" meaning any skin condition except for mpox. These studies have yet to differentiate or identify mpox against specific skin lesions, and though having an "other" category gives information to patients, it does not offer a result that can be acted upon, other than that the patient is aware that they do not have monkeypox. Moreover, herpes zoster, which is known to be mistaken for mpox, was not explicitly noted to be included in the datasets of either of the two studies discussed. Considering to distinguish monkeypox from a commonly confused skin lesion type that has yet to be differentiated from mpox in these studies, such as herpes zoster, could lead to more directional, efficient medical decisions being made.

In order to lessen the burden of monkeypox around the world and promote the spread of correct public health information, a deep learning model and mobile application prototype that identifies skin lesions as either monkeypox or herpes zoster will be developed and tested in a feasibility study. Beginning by gathering images of monkeypox and herpes zoster viral lesions on the limbs, abdomen, and face followed by the development of a deep learning model taught using these images, the application will be tested on a separate cohort of images with the goal of becoming a novel point of care system for healthcare professionals to consider utilizing. By the end of this study, the following research question will be sought to be answered: How can deep learning be applied to a mobile application to distinguish monkeypox viral lesions from herpes zoster viral lesions? To answer this research question, the project goal developed is to develop a deep learning model and prototype that could later be integrated into a functional mobile application.

Methods

Engineering Design Method

The engineering method is a six-step process that engineers and product designers utilize to guide the development of devices, infrastructure, and tools. Beginning with the first phase of establishing a problem, a problem is identified with a possible solution; in this phase, the main objectives are to define a broad problem of concern, assess its validity, gauge its feasibility, and identify an end user who will seek the solution (Lasser, n.d.). Related to this topic of inquiry, the defined problem was the poor diagnosis of monkeypox based on its lesions' similarities to that of the herpes zoster virus, with the end user being patients or clinicians in medical settings. During the first stage, a research question, varying in broadness, is inquired upon. As mentioned previously, the current research question is as follows: How can deep learning be applied to a mobile application to distinguish monkeypox viral lesions from herpes zoster viral lesions?

Secondly, researchers must analyze current concepts in the problem's field. This includes a deep analysis of current solutions to the problem, if any, and related works that contributed to partial or complete solutions to the research question (Lasser, n.d.). During this process, researchers must also consider the requirements of their product as well as the constraints that are required in the design (Lasser, n.d.). For instance, while studying sources related to the problem, two sources were discovered that related to monkeypox skin rash analysis and app development, both of which tested a mobile application that identified images as positive or negative for monkeypox infection (Sahin et. al, 2022; Ali et. al, 2022). This allowed a gap in research to be thoroughly identified as well as serve as a foundation for future testing techniques and experimental designs.

Thirdly, researchers must plan the development of their product, device, or tool. This includes assigning tasks for different members of the team, creating a budget, and forming a planned timeline of development to keep the project on track in terms of time (Lasser, n.d.). Relative to this investigation, time frames for data collection and testing the deep learning models were created. During this stage, numerical requirements, such as the amount of cloud storage required for the app, are identified (Lasser, n.d.). The table below displays the constraints considered in this engineering investigation:

Table 1. Circumstantial and Design Constraints

Circumstantial Constraints	Design Constraints
1. Development within six month period	1. Small-sized mobile application (less than 35 MB)
2. Programming software compatible with MacBook Air laptop	2. Available on iOS and android devices
3. Less than 200 images for data collection	3. Simplistic user flow

Throughout the brainstorming process, the fourth step in this method, researchers hone in on ideas to begin curating a solution to the problem. In the fifth step, the solution is designed, developed, and prototyped (Lasser, n.d.). A unique attribute of this methodology is its ability to return to previous steps to build upon the design (Lasser, n.d.). This method consists of designing, testing, debugging, and redesigning the product (Lasser, n.d.). As a result, many engineers undergo the design and development process multiple times to ensure that the most accurate and efficient product is developed (Lasser, n.d.). Finally, in the launching phase, the sixth and final stage of this method, the proposed product is introduced to companies and manufacturers in a presentation or final paper (Lasser, n.d.). In the following paragraphs, the fourth and fifth steps of the engineering method are more thoroughly discussed in regard to this engineering investigation.

Prototype Development

In order to fully understand the goals and purpose of this mobile application, a basic prototype was developed using the mobile application prototype website MarvelApp. Through this website, various features of the application were determined. By the end of the prototyping process, a draft prototype was created to serve as a basic guideline for software development (Figure 2). Prior to developing the prototype, a basic flowchart was created to serve as an overview of the predicted user flow of the mobile application (Figure 1). These two designs helped translate brainstormed ideas into a more structured design for the development process.

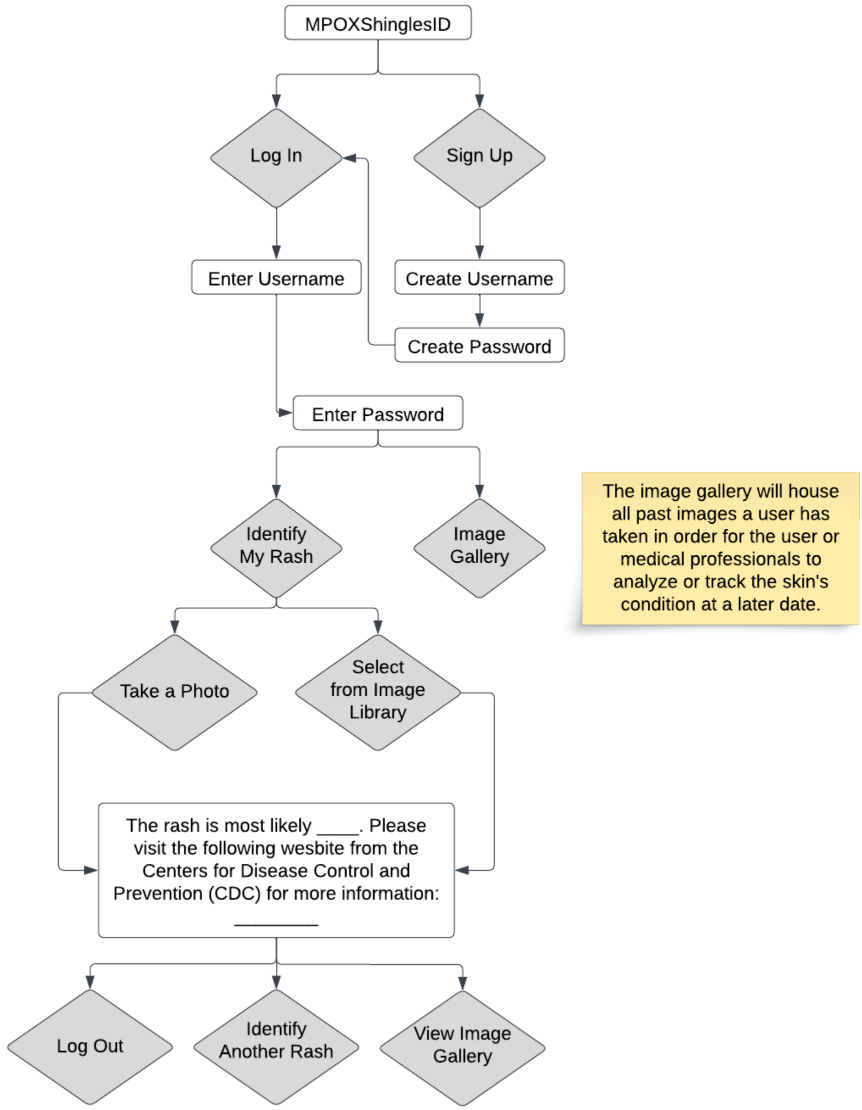

Figure 1. Image of Application Flowchart

Figure 2. Image of Prototype Homescreen

Data Collection

Multiple image datasets from previous studies were utilized in this study to gather additional images. These datasets served as additional data to aid in the creation of a fully functional image classification system. The herpes zoster image dataset comprised a random subset of images from a January 2021 study performed by researchers at the Gwangju Institute of Science and Technology testing the diagnosis of herpes zoster utilizing a mobile application (Back et al., 2021). With the permission of lead researcher Seunghyeok Back, this dataset was used to represent images of herpes zoster in this study.

Furthermore, monkeypox images were gathered from two public datasets titled the Monkeypox Skin Lesion Dataset (MSLID) from 2022 research led by Shams Nafisa Ali, and the Monkeypox Skin Image Dataset (MSID) from computer science and medical researchers associated with Harvard University and Northern University Bangladesh (Ali et al., 2022; Islam et al., 2022). For both the monkeypox and herpes zoster datasets, additional images of cases of these lesions on more pigmented skin tones were gathered from public studies, new websites, and medical-based websites were collected to ensure that all image categories represented diverse cases of herpes zoster and monkeypox.

Because of the recency of the monkeypox pandemic, monkeypox images required cross-checking to ensure that they were actual monkeypox skin lesions. Images were gathered, and their hyperlinks were stored in Google Docs. Next, these downloaded images were transferred to a Google Spreadsheet. Consulting with expert advisor Dr. Cristina Thomas, an Assistant Professor of Internal Medicine and Dermatology and a practicing dermatologist with a specialization in infectious skin conditions at the UT Southwestern Medical Center, images were cross-checked to ensure that the images were monkeypox lesions. The confirmed images were then placed in a "Monkeypox" folder on the

MacBook Air laptop utilized in this study. Because of the nature of the herpes zoster being used in previous studies, these images were not cross-checked and were immediately downloaded and placed in a folder titled "HZV".

After categorizing the images, they were further organized into three categories: training, validation, and testing, each with their respective folders and subfolders (Figure 3). The training category included seventy percent of the images from each category. The validation and testing images were split equally and placed in their respective folders, with fifteen percent of the images allotted to each category. In deep learning, the training set is the set of images from which a deep learning model learns. The validation set is utilized to estimate the performance of a model on images it has not seen before, and the testing set is utilized to calculate the model's accuracy in a tested realistic setting. In this investigation, the images of both mpox and herpes zoster were gathered and split with 70 percent of images in the training set, 10 percent of the images in the validation set, and 20 percent of the images in the testing set, which is a common ratio in deep learning investigations in order for the deep learning model to be thoroughly trained.

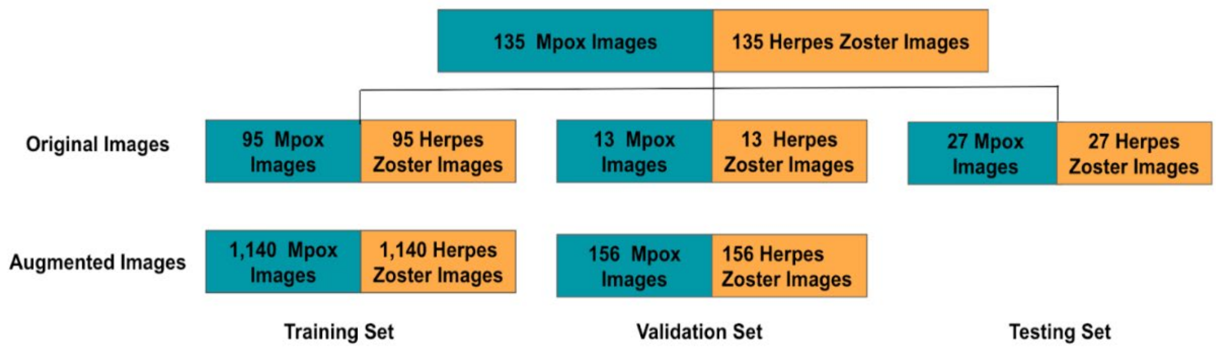

Figure 3. Data Collection Division and Augmentation of Training, Validation, and Testing Sets

Due to the time and resource constraints in this investigation, 135 images of both skin diseases were collected, which is small in comparison to larger studies at the university and post-university levels. As a result, image augmentation, the process of editing images to expand a dataset, was utilized. The images in both categories were increased by 12-fold, or 12 times, through a series of data editing techniques, including shear, random brightness, random rotation, inversion, gaussian filters, and random color (Figure 3).

Transfer Learning of Deep Learning Model

Using the pre-trained model, MobileNetV3, the augmented images were trained over the course of two weeks. Throughout the training process, the deep learning model was altered and experimented upon in order to achieve the most accurate results possible. Following training, the images were validated utilizing new images before being tested with the remaining images. This process was repeated using another pre-trained model known as ResNet50, and its testing results were compared against the results of MoblieNetV3. These deep learning models were selected due to their specialization as a CNN as well as through use in previous deep learning-related works in the field of dermatology (Ali et al., 2022). Due to the specificity of these models, it is important to utilize deep learning models known to perform highly for specific purposes.

Development of Prototype

To address the final stage of the engineering design process, a prototype was created utilizing MarvelApp. The decision to utilize Marvel App was mainly due to its efficiency. Due to the short time period of this investigation, creating a fully-functional application was not realistic, and to ensure that the software was accurate, it was decided to focus on developing deep learning models that could later be integrated into a mobile application in future explorations of this topic.

Results

The accuracy of both MobileNetV3 and ResNet50 were analyzed by graphing the percentage values of accuracy, validation accuracy, loss, and validation loss across the testing period, labeled by epoch, which is a unit of measurement of passing a dataset entirely through an algorithm ("Splitting Into Train, Dev and Test Sets", n.d.). In this study, 20 epochs were utilized. Accuracy represents the correctness of the training data, where a value closer to 1.000 represents higher accuracy ("Splitting Into Train, Dev and Test Sets", n.d.). Validation accuracy follows the same concept, except for representing the accuracy of the validation set ("Splitting Into Train, Dev and Test Sets", n.d.). The loss represents how poorly the model performed per image in a training set, with a value closer to 0.000 representing higher performance. The validation loss is the same, except that it illustrates the loss of the validation set. Validation loss and accuracy are heavily relied upon to predict the real-world performance of a deep learning model, as these images are not used to train the model ("Splitting Into Train, Dev and Test Sets", n.d.). In the figures that follow, validation loss is labeled as "val_loss" and validation accuracy is labeled as "val_accuracy".

MobileNetV3 Performance

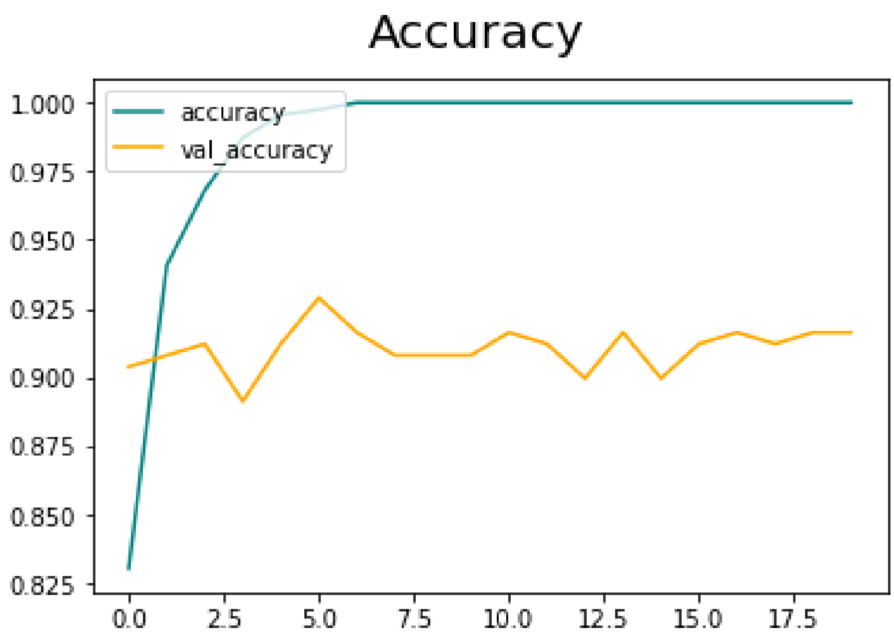

Figure 4. Accuracy of Training and Validation Sets of MobileNetV3

Following fine-tuning, MobileNetV3's performance in training, testing, and validation was extremely successful. In the figure above, the model's accuracy and validation accuracy is displayed (Figure 4). Over the training period, the MobileNetV3 accuracy rate increased exponentially before stabilizing at an average accuracy of 100 percent (see Table A3). The validation accuracy also expressed promising results, maintaining an average accuracy between 89 percent and 93 percent throughout its testing.

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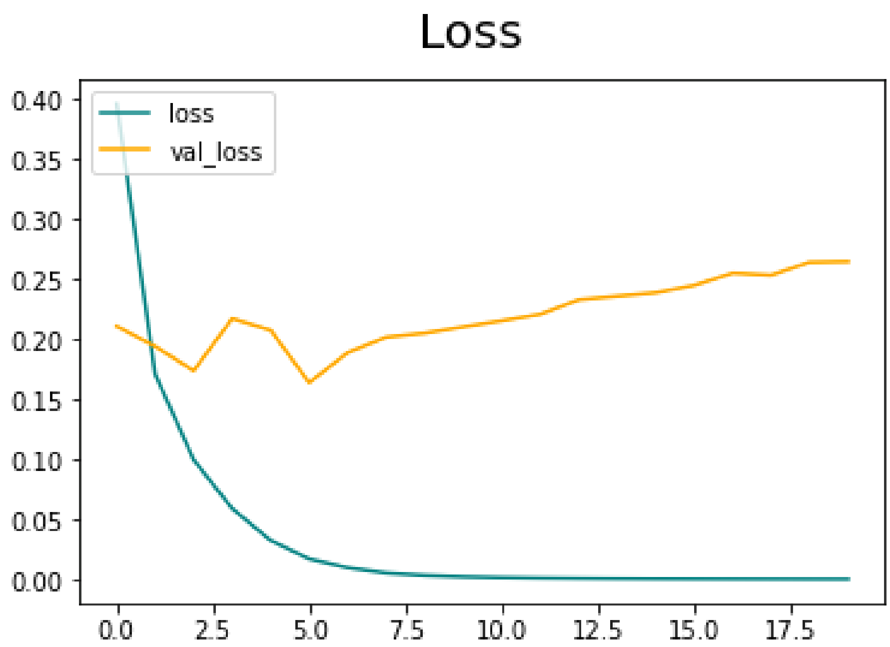

Figure 5. Loss of Training and Validation Sets of MobileNetV3

The figure above displays MobileNetV3's loss and validation loss (Figure 5). The model's loss decreased exponentially, stabilizing at two percent. Though the model's validation loss fluctuated, it maintained an average loss between 16 percent and 26 percent, which represents promising performance for real-world applications. When tested on the testing dataset, MobileNetV3 maintained an accuracy rate of 93.10 percent with a loss of 29.30 percent (see Table A4).

ResNet50 Performance

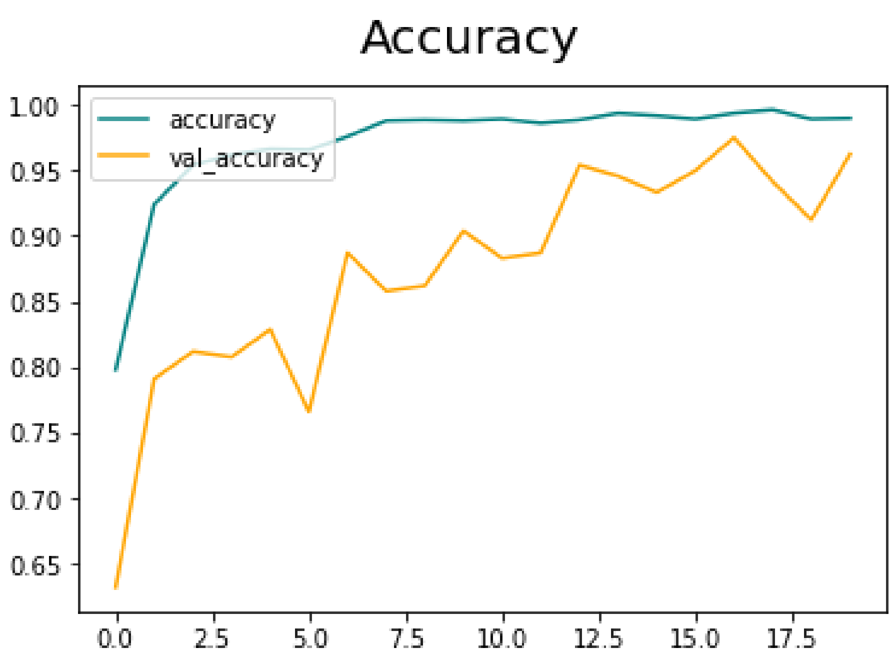

Figure 6. Accuracy of Training and Validation Sets of ResNet50

Similar to MobileNetV3, ResNet50 also displayed promising performance when tested on the same dataset of training, validation, and testing image sets. The figure above displays the model's accuracy and validation accuracy (Figure 6). Over the training period, the ResNet50 accuracy rate increased exponentially before stabilizing at an average accuracy of 99 percent (see Table A1). The validation accuracy also expressed favorable results, maintaining an average accuracy between 65 percent and 93 percent throughout its training.

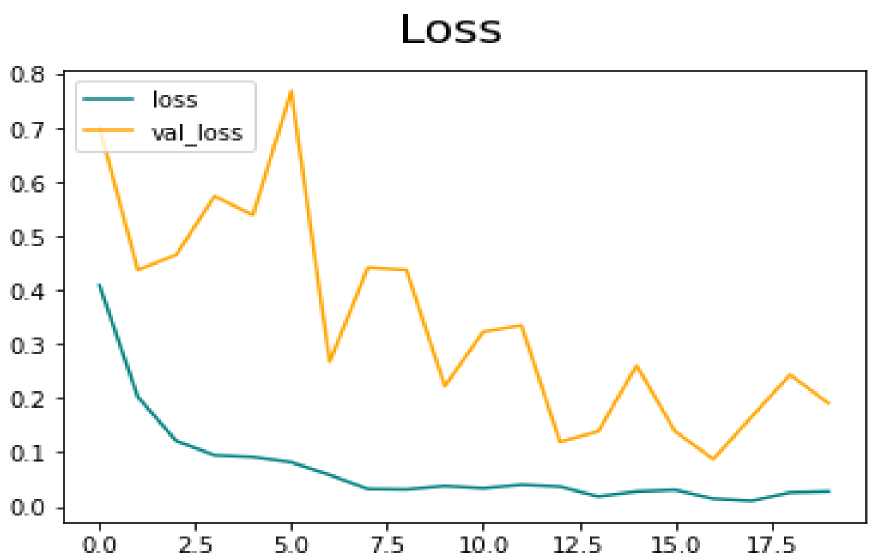

Figure 7. Loss of Training and Validation Sets of ResNet50

Above displays a figure of ResNet50's loss and validation loss (Figure 7). The model's loss decreased exponentially, reaching as low as three percent (see Table A1). Though the model's validation loss fluctuated at large rates, it maintained a loss percentage between 11 percent and 77 percent. During testing, ResNet50 maintained an accuracy rate of 93.10 percent with a loss of 17.02 percent (see Table A2).

Comparison of Performance

Regarding accuracy, the training accuracy of MobileNetV3 and ResNet50 appeared to be quite similar, as they both increased exponentially to extremely high accuracy. However, ResNet50 performed stronger compared to MobileNetV3, as its validation accuracy was marginally greater than MobileNetV3, and ResNet50's validation loss reached a lower range, as noted in the graphs above. Because validation accuracy and loss determine the performance of a model on data it has not viewed previously, ResNet50 was chosen in order to ensure that the mobile application maintained the highest performance possible when given data in a real-world setting. ResNet50's testing loss confirmed this decision, having a percent loss 17.28 percent lower than MobileNetV3's percent loss.

Mobile Application Prototype

Following testing the performance of the deep learning models, an end-user prototype was developed utilizing MarvelApp for iOS and Android use and downloaded onto an iPhone 14 Pro for further viewing. Below displays the prototype home page of the mobile application prototype (Figure 8). Beginning with the home page, a user is able to navigate to take a photograph of their lesion or be directed to more information regarding monkeypox or herpes zoster virus. If a user wishes to have their image identified, they would choose an image from their photo library and submit the photo. The result of the lesion's condition will be given, followed by more information regarding recommended steps to take for more information and how to seek clinical confirmation of the skin lesion's diagnosis (see Appendix B).

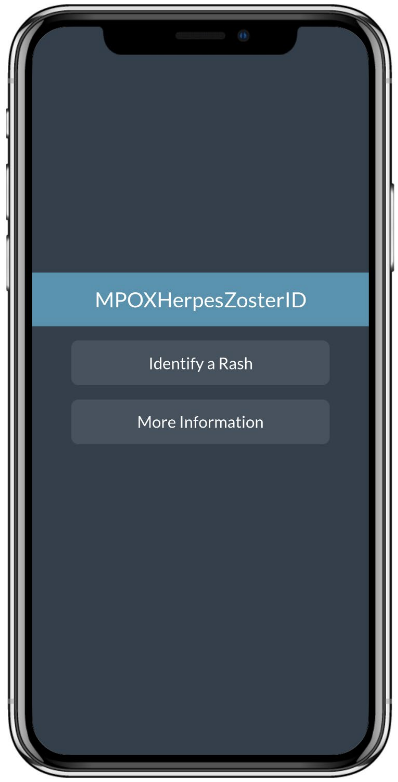

Figure 8. Image of Final Mobile Application Home Screen

Discussion

In this study, the initial research question inquired upon was as follows: How can deep learning be applied to a mobile application to distinguish monkeypox viral lesions from herpes zoster viral lesions? To answer this research question, the project goal created was to develop a deep learning model using transfer learning to program a functional mobile application prototype. Over a six-month period, images were collected and augmented, and two deep learning models, MobileNetV3 and ResNet50, were trained and fine-tuned for accuracy. The higher-performing model, ResNet50, was considered when creating a mobile application prototype displaying end-user use.

In regards to the research question, this investigation exhibited promising results, with both models attaining a final test set accuracy of 93 percent, which is comparable to related studies in the dermatological field (Sahin et al., 2022; Ali et al., 2022). However, further research is needed to conclude that continuing to develop a fully-functional mobile application is reliable for medical use due to limitations in dataset size, models chosen, and the lack of clinical trial use.

Limitations

In most deep learning-based applications, thousands of images are tested to ensure versatility in the application's accuracy across various images to replicate real-world variety. Due to the timeline of this investigation, the data collection period was shortened to ensure that the project completion would conclude in alignment with the nine-month-long course of AP Research. As a result, a smaller amount of images were collected and trained upon, possibly leading to generalized results; further testing with larger image datasets could lead to results that would ensure that findings are accurate and reliable for real-world applications.

Furthermore, only two deep learning models were utilized through transfer learning. In past studies, additional deep learning models, such as VGG-16 and Inception V3, were utilized (Sahin et al., 2022; Ali et al., 2022). Testing a variety of deep learning models ensures the best model is utilized for a specific dataset, leading to a more advanced, efficient mobile application being developed. Due to time constraints and the disk size of the laptop used in this investigation, only two deep-learning models were tested.

Finally, the mobile application prototype was not tested by a patient or dermatologist. In more advanced studies, testing by a doctor or other physician can offer a more robust analysis of a mobile application; this can facilitate improvements to the mobile application to develop a more efficient, user-friendly application. Due to the nature of a high school-level investigation, the prototype was not tested by a medical professional or patient, which may have offered more insight into the development of this mobile application.

Implications and Future Research

The results of this feasibility study support past research regarding the effectiveness of mobile application intervention in dermatology. Similar to the studies mentioned previously involving skin conditions ranging from acne to cancer, this investigation offers yet another successful application of deep learning in aiding in the identification of skin lesions while filling a research gap by providing the identification of two relevant viral skin conditions.

As the medical field evolves into a more technology-driven facet of society, it is important to seize this opportunity of technology in regard to dermatology by taking advantage of dermatology's visual nature which a computer can analyze. With this, the investigation widens the limitations of dermatology in regard to viral skin lesions. Following the COVID-19 pandemic and the monkeypox epidemic, it is now known how crucial it is to act quickly and spread accurate information efficiently to the greater public. This investigation helps to consider using technology to communicate effective public health recommendations when viral testing or infectious-disease-specializing physicians are unavailable. Though the small-scale nature of this study requires further research, it offers a new possibility of further spreading accurate public health information that could combat misinformation and misdiagnosis while leading to the correct steps being taken, such as self-isolation. On a larger scale, such information could prevent or subside epidemics and pandemics from erupting or reaching other counties, regions, countries, or continents, benefiting public health on a global scale.

With further testing and additional improvements, the current mobile application could be utilized in clinics or hospital facilities lacking high medical knowledge of skin conditions. Forms of this mobile application in combination with other aspects of pre-existing mobile applications could lead to patients and doctors having access to a broad variety of diagnoses. Future research could include applying this investigation utilizing viral skin conditions common to a different region or experimenting with different deep-learning models to compare their effectiveness. This investigation's results aid the medical community in being one step closer to the possibility of creating an all-purpose application to identify dozens of viral skin lesions found globally or common to a specific country, region, or continent in the future, allowing efficient dermatological advice to be provided across the world.

Acknowledgments

Firstly, I would like to thank my teacher, Mrs. Sinclair. Throughout my AP Capstone journey, Mrs. Sinclair has given nothing but support and guidance throughout my academic journey in both the AP Seminar and AP Research. I would also like to thank my mentor, Dr. Thomas; she helped me to truly situate my research by keeping a medical and dermatological context in mind throughout this investigation. Finally, I would like to thank my mother, father, and sister for constantly supporting, uplifting, and encouraging me to pursue my dreams.

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