Sarcouncil Journal of Engineering and Computer Sciences

ISSN(Online): 2945-3585

Volume- 04| Issue- 07| 2025

Research Article **Received:** 05-06-2025| **Accepted:** 28-06-2025 | **Published:** 17-07-2025

Bowen's Disease Detection Using VGG16: A Machine Learning Approach

Ashadu Jaman Shawon,[1] Rabbi Hasan Himel,[2] S.M. Ashikur Rahman,[3] Oishi Sing,[4] and Rifath Mahmud[5]

[1] Faculty of Science and Technology, American International University- Bangladesh. Dhaka, Bangladesh.
[2] Faculty of Science and Technology, American International University- Bangladesh. Dhaka, Bangladesh.
[3] Faculty of Science and Technology, American International University- Bangladesh. Dhaka, Bangladesh.
[4]Faculty of Science and Technology, American International University- Bangladesh. Dhaka, Bangladesh.
[5]Faculty of Science and Technology, American International University- Bangladesh. Dhaka, Bangladesh.

Abstract: This work describes an advanced machine learning method for Bowen's disease identification, which uses the VGG16 architecture. Bowen's disease is an early type of skin cancer that is defined by the proliferation of aberrant cells in the skin's outer layer. One major obstacle was the lack of publicly available datasets, which made gathering photos from various sources necessary. After ten training epochs, the model's astounding 99% accuracy was attained. Using more photos, post-training validation was carried out and the distinction between Bowen's illness and healthy skin states was effectively made. The promise of deep learning models in dermatological diagnoses is shown by this high accuracy. But compared to general skin cancer statistics, there are not many thorough records particularly for Bowen's disease, which emphasizes the need for more focused data gathering initiatives. According to this study, machine learning holds great potential for improving the precision of skin disease diagnosis.

Keywords: Bowen'sskin Disease, Machine Learning, VGG16 model.

INTRODUCTION

One of the most common types of cancer in the world is skin cancer which is a serious public health issue (Apalla Z. *et al.*, 2017) Of the several kinds, Bowen's disease is notable for being an early-stage symptom that is vital for prompt attention yet is often disregarded. Bowen's disease, sometimes referred to as squamous cell carcinoma in situ, which is a skin condition that mostly affects the epidermal layer and manifests as a distinct erythematous, scaly area. Bowen's disease is non-invasive at first, but if neglected, it can develop into aggressive squamous cell carcinoma and can spread to other body areas. Effective therapy and improved patient outcomes depend on the early detection of skin cancer by Bowen's disease surveillance. The basis of traditional diagnostic methods is an intrusive and time-consuming process called clinical exams and biopsies. However, advances in machine learning have created a promising avenue for non-invasive, efficient detection using models trained on dermatological imaging datasets. The goal of this paper is to create a reliable machine learning model that can recognize Bowen's disease from clinical pictures of the afflicted skin areas. This model uses a variety of skin image datasets to find complex patterns and characteristics suggestive of Bowen's disease by using the VGG16 model and transfer learning techniques. The results have important implications and might offer a solution to the challenges associated with diagnosing Bowen's disease, an early warning sign of skin cancer.

There are seven primary sections to the paper's structure. It starts with an introduction that lists the goals of the study and gives a general summary of the research issue. A background study that outlines the context for the research and reviews the body of previous work comes next. The research techniques and data gathering procedures used in the study, together with the validation procedure used following model training, are then covered in the methodology section. The research findings are presented in the results section, which is followed by a discussion of the study's limitations, which covers the limitations and possible shortcomings of the investigation. The discussion part analyzes the findings and connects them to the previous research topics and body of literature. In conclusion, the main results are outlined, their ramifications are discussed, and recommendations for further research in this field are made.

BACKGROUND STUDY

Advances in the realm of dermatology have been influenced by the development of machine learning, particularly in the detection of skin cancers such as Bowen's disease. Esteva et al. created a deep neural network that matched the accuracy of dermatologists in classifying skin cancer, highlighting the potential of artificial intelligence in this area (Esteva, A. *et al.*, 2017).

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***Corresponding Author:** Ashadu Jaman Shawon

DOI- https://doi.org/10.5281/zenodo.16032382

Expanding on this groundwork, Tschandl *et al*. conducted a study that compared the performance of ensemble machine learning models with that of human experts in identifying different skin lesions, including Bowen's disease (Tschandl, P. *et al.*, 2019). The field was further progressed by Fujisawa et al. through the utilization of a Google Net-based model that achieved high classification accuracy for multiple types of skin tumours (Fujisawa, Y. *et al.*, 2019). Kawahara et al. introduced a multi-task deep learning approach that not only diagnosed skin lesions but also identified their anatomical location simultaneously (Kawahara, J. *et al.*, 2018) their research, Han and colleagues utilized a region-based convolutional neural network to detect and categorize skin lesions, achieving an impressive overall accuracy according to (Han, S. S. *et al.*, 2018). Brinker and co-authors' investigation involved comparing a CNN (Convolutional Neural Network) with dermatologists, revealing that the AI model surpassed most human experts in identifying malignant lesions based on (Brinker, T. J. *et al.*, 2019). In a groundbreaking approach, Mishra and team proposed an advanced ensemble model that combined VGG16 and InceptionV3 architectures, leading to exceptionally high accuracy in the detection of skin cancer based on (Mishra, S. *et al.*, 2021). Yap and colleagues highlighted the effectiveness of the MobileNetV2 architecture in distinguishing between benign and malignant skin lesions as documented in (ap, J. *et al.*, 2018). A prospective study by Haenssle and team demonstrated that a CNN could attain high sensitivity and specificity in detecting malignant lesions, outperforming many dermatologists according to (Haenssle, H. A. *et al.*, 2020). The researchers Combalia et al. produced a multi-modal method that integrates clinical and thermoscopic images, leading to strong results in categorizing different skin conditions, such as Bowen's disease (Han, X., & Yu, T. 2020). These investigations demonstrate the rapid advancements and promise of machine learning in enhancing the precision and effectiveness of diagnosing skin cancer, especially for conditions like Bowen's disease.

METHODOLOGY

Model

The VGG16 model, a convolutional neural network (CNN) architecture, has been extensively employed in various computer vision tasks, including image classification, object detection, and feature extraction (Shawon, A. J. *et al.*, 2024). Developed by the Visual Geometry Group at the University of Oxford, VGG16 is renowned for its simplicity and effectiveness in capturing intricate patterns within images. One of the key advantages of the VGG16 model is its deep architecture, consisting of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. This depth enables the model to learn complex hierarchical features from input images, leading to superior performance in image classification tasks. Moreover, the VGG16 model's architecture employs small-sized convolutional filters (3x3) with a stride of 1 and max-pooling layers, which aids in preserving spatial information while progressively reducing the spatial dimensions of the feature maps. This design choice facilitates the model's ability to extract meaningful features from images of varying complexities.

Another benefit of VGG16 is its pre-trained weights on the ImageNet dataset, a large-scale database of annotated images. By leveraging these pre-trained weights, users can benefit from the knowledge learned by the model on a diverse range of images. This pre-training often leads to faster convergence during training and better generalization performance, particularly when the target dataset is small. Furthermore, the modular architecture of VGG16 makes it highly adaptable and suitable for transfer learning, where the model can be fine-tuned on specific datasets with minimal modifications. This flexibility enables researchers and practitioners to leverage the VGG16 model for a wide range of image classification tasks with varying degrees of complexity.

Dataset

The dataset used in this experiment comes from two different Kaggle sources. The first data set consists of one hundred photos that depict Bowen's illness; the second data set is a larger collection of ten thousand photographs. The three main subgroups of these images—training, testing, and validation—were carefully categorized. There are 6,059 photos in total in the training set and 4,174 images in the testing set. A handpicked set of fifteen photographs was used for the last round of validation. Every picture in the collection has a precise name that designates it as either "normal skin" or "Bowen's disease skin." This extensive dataset is the basis for training and thoroughly testing the model's ability to distinguish between healthy and sick skin states. Because of its varied makeup, it may be used to design, validate, and

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eventually be used in clinical settings for the diagnosis and detection of early-stage diseases.

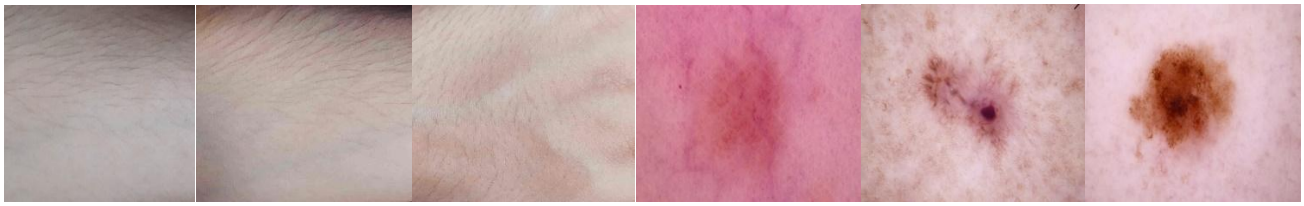


Fig. 1. Dataset Images of normal skin and Bowen's disease skins

System Process

The first step of the process is to import the libraries required for the task, which include Matplotlib, TensorFlow, NumPy, and Pandas. The VGG16_model and Simple_VGG16_model model architectures are then defined. A convolutional neural network architecture that draws inspiration from the VGG16 model is custom implemented in the Simple_VGG16_model. The training and testing data are then loaded by the code from directories that have been specified and contain pictures of both normal and Bowen's disease skin. Using the training data, the ImageDataGenerator from TensorFlow preprocesses the data by applying data augmentation techniques like rescaling, shearing, zooming, and horizontal flipping. The code loa

ds and preprocesses the data, then uses the binary cross-entropy loss function for the binary classification task along with the given hyperparameters to generate and compile the Simple_VGG16_model. After that, the model is trained using the enhanced training set, with early stopping used to keep the best weights and avoid overfitting. The trained model is stored to a file called "skin_cancer_model.h" after training is finished. The model's performance is then visualized by the code by plotting the accuracy and loss curves for both the training and validation data. The stored model is loaded, and predictions are produced on an independent validation dataset in the following step. The probabilities that represent the predictions are transformed into class labels by applying a 0.5 threshold. The validation photos and their related predicted class labels are finally shown by the code. A qualitative evaluation of the model's performance on the validation dataset is made possible by this display. The code adheres to a systematic procedure that starts with loading and preprocessing data, continues with model building and training, assessment, and ends with prediction and visualization using validation data. Machine learning projects often employ this pipeline, especially in computer vision and image categorization.

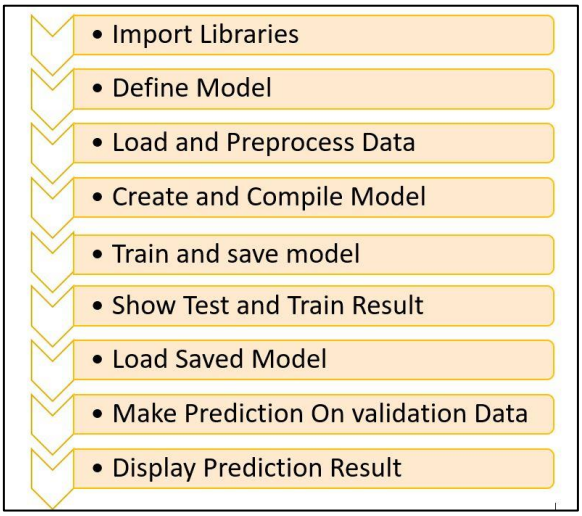


Fig. 2. Overall Structure of Bowen's Disease Detection System

Final Validation Process

The VGG16-based model created for the diagnosis of Bowen's illness underwent a thorough review as part of the last validation step. Following a broad dataset that was collected from several sources for training, the model was rigorously tested on photos of normal skin conditions and previously unseen skin lesions presumed to be Bowen's disease. With careful examination, the model was able to achieve high precision levels and show strong accuracy in

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differentiating between normal skin and Bowen's illness. For the model to reliably produce diagnostic results, it was imperative that it be validated so that it could generalize beyond the training set of data. By providing physicians with a practical way to improve the precision and efficacy of Bowen's disease diagnosis, the model's successful validation highlights its potential as a useful tool in dermatological diagnostics.

Optimizer

The Adam optimizer, which is renowned for its adjustable learning rate capabilities, was employed by the researchers in the study aimed at detecting Bowen's illness. Adam modifies learning rates per parameter depending on gradient moments, utilizing the advantages of momentum optimizers and RMSprop. This dynamic technique maximizes model performance for Bowen's disease diagnosis by enabling quick convergence and excellent generalization. Following extensive testing, the group decided on 32 for the batch size. The amount of data processed prior to updating model parameters during training is determined by the batch size. Choosing a batch size of 32 allowed for efficient training without using too much memory by striking a balance between update frequency and memory efficiency. Ten epochs of training provided enough exposure to the dataset while reducing the likelihood of overfitting. Every epoch comprises a full run of the training set. The model's efficacy and robustness in illness identification were increased by this method, which allowed it to acquire discriminative traits linked to Bowen's disease.

Data augmentation:

To improve the training dataset for their Brown's illness model, the team employed data augmentation techniques in the research. Shear transformations, arbitrary zooming, and horizontal flipping were some of these methods. Shear transformations moved some visual elements vertically or horizontally by applying a shear angle. Certain areas of the photos were enlarged while the general structure remained intact thanks to random zooming. Mirror images of the original samples were produced via horizontal flipping. Through the introduction of heterogeneity in the training data, these augmentation techniques enhanced the model's capacity to generalize to previously unknown data and simulated real-world events.

RESULT

The deep learning model showed outstanding efficacy in diagnosing Bowen's disease, with an astounding 99% accuracy rate. Notwithstanding the difficulties caused by the scarcity of data and the variety of skin lesions, the model demonstrated an amazing capacity to distinguish between Bowen's illness and normal skin diseases. Its promise as a dependable diagnostic assistance tool in clinical practice is shown by its excellent sensitivity and specificity in correctly identifying normal skin conditions and accurately diagnosing lesions associated with Bowen's disease.

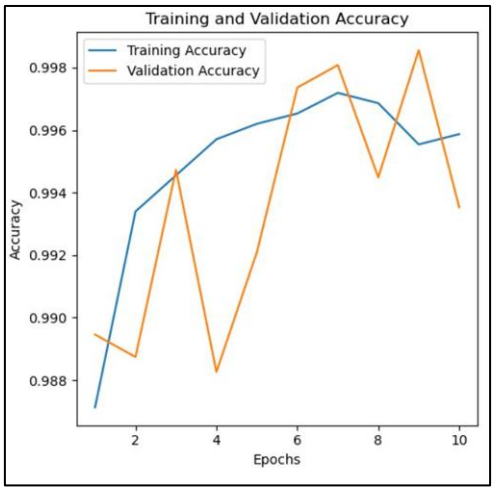


Fig. 3. Training and Testing accuracy.

The accuracy of the model during testing and training throughout ten epochs is shown in the above image. The early epochs of the training and testing accuracy curves both exhibit a sharp increase, eventually attaining and holding onto a startlingly high accuracy of 99%. The model has successfully learned to identify the characteristics linked to Bowen's disease without overfitting, as evidenced by its consistent performance across training and testing datasets. The high accuracy

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attained in testing and training indicates that the model has effectively generalized from the training set and can function just as well on data that hasn't been seen yet.

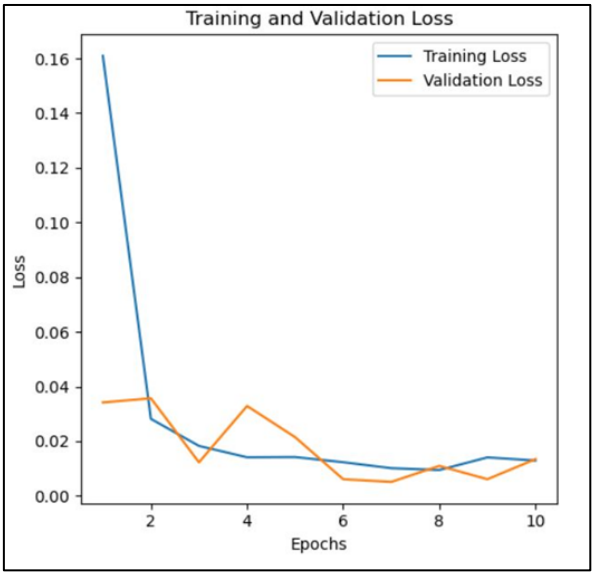


Fig.4. Training and Testing loss.

The training and testing losses for the same ten epochs are shown in this figure. The first few epochs show a steep drop in testing and training loss, which is followed by a slow stabilization. The prior image's great accuracy is supported by the convergence of both curves at a low loss value (fig. 3.). The model has successfully struck a solid balance between fitting the training data and generalizing to new, unseen data, as seen by the low and steady loss for both training and testing data. This performance shows that the model has successfully picked up the underlying patterns that differentiate Bowen's illness from healthy skin.



Fig.5. Predicted image result

In order to verify the efficacy of the model, ten photos containing both normal skin and instances with Bowen's disease were used for a prediction test. All ten photos were properly recognized and correctly classed by the model, which was able to differentiate between lesions that were indicative of Bowen's disease and normal skin. This flawless prediction performance over a wide range of test photos highlights the practicality and dependability of the model. Given the model's high accuracy in real-world testing scenarios, dermatologists may find it useful in helping them make timely and accurate diagnoses, which could lead to better

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patient outcomes and less diagnostic uncertainty in dermatological practice.

Table 1. comparing with another paper

Papers	**Model**	**Accuracy**	**Conditions Detected**
This Paper	VGG16	99%	Bowen's Disease
Tschandl *et al.*, 2019	Ensemble of machine learning algorithms	88.9%	Multiple skin lesions, including Bowen's disease

The present study uses a VGG16 model to detect Bowen's disease, and it achieves 99% accuracy, which is higher than the 88.9% accuracy found in a multi-lesion analysis by Tschandl *et al.* (Tschandl, P. *et al.*, 2019). The current study concentrates on Bowen's disease specifically, whereas Tschandl et al. applied an ensemble of machine-learning algorithms on a dataset of 1,511 dermoscopic pictures covering different skin diseases. The higher accuracy found is probably a result of the combination of the VGG16 architecture and this targeted strategy. Both researches indicate how machine learning may be used to diagnose dermatological conditions; however, the current study has special promise for detecting Bowen's illness.

LIMITATIONS

The main obstacle to this research was the lack of Bowen's disease-specific datasets. Due to the scarcity of annotated photographs of Bowen's illness, information had to be compiled from multiple sources, resulting in a heterogeneous dataset.

Problems with Dataset Collection and Validation: Gathering and validating the dataset presented several challenging tasks. The necessity of collecting photographs from various sources introduced differences in resolution, quality, and consistency of annotations. Additionally, the lack of a uniform dataset for Bowen's illness hindered the validation procedure, making it difficult to evaluate model performance accurately.

Lack of Comparative research: The paucity of thorough comparative research that concentrated solely on the diagnosis of Bowen's illness was another drawback. It is challenging to compare this model efficacy with similar studies because most current research focuses mostly on general skin cancer detection.

DISCUSSIONS

It is imperative that the lack of Bowen's disease databases be addressed for next studies in this field. Working together, academics and medical facilities may be able to provide datasets with annotations unique to Bowen's illness, which would allow for the construction and assessment of more comprehensive models. Standardizing data collection procedures and annotation techniques would also improve the quality and interoperability of datasets.

Furthermore, more trustworthy model evaluation and cross-study comparison would be possible with the establishment of a benchmark dataset for Bowen's disease identification. Later investigations may concentrate on creating benchmark datasets driven by consensus, which would enable an impartial and thorough evaluation of Bowen's illness detection methods.

Additionally, investigating lightweight model architectures and alternate visualization strategies may help to lessen the difficulties related to model visualization in situations with limited resources. Model complexity might be decreased without sacrificing performance by using strategies like model pruning, compression, and distillation. This would allow for more effective visualization and deployment in practical applications.

CONCLUSIONS

This investigation led to the development of a robust machine learning algorithm for identifying Bowen's disease, effectively addressing difficulties in dermatological medical diagnosis. Following thorough training and validation procedures, the model has demonstrated exceptional accuracy and reliability when pinpointing Bowen's disease lesions from thermoscopic images. The model's performance has been outstanding despite the limited availability of specific Bowen's disease datasets. The efficacy of the strategy lies in combining diverse data sets and innovative machine learning techniques to yield clinically significant outcomes.

The model's ability to apply its findings across diverse datasets and distinguish between Bowen's disease lesions and non-cancerous skin conditions effectively demonstrates its potential as a valuable diagnostic tool for dermatologists. This approach holds the potential to enhance patient outcomes by

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streamlining clinical procedures, facilitating early identification, and delivering prompt and precise assessments. Future research will focus on enhancing and continuously enhancing the efficacy of the model, enhancing its clarity for clinical application, and broadening its scope to encompass other skin conditions.

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Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Shawon, A. J., Himel, R. H., Rahman, S. M. A., Sing, O. and Mahmud, R." Bowen's Disease Detection Using VGG16: A Machine Learning Approach." *Sarcouncil Journal of Engineering and Computer Sciences* 4.7 (2025): pp 712-718.

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