Article

Enhancing Diagnostic Accuracy with SE-Inception Model Integration in Pressure Ulcer Detection

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AIM: Pressure ulcers are a prevalent health concern, often leading to severe complications if not diagnosed and treated promptly. This study introduces the Squeeze-and-Excitation (SE)-Inception model, which integrates SE blocks into the Inception architecture, aiming to enhance classification performance in medical image analysis.
METHODS: The performance of the SE-Inception model was compared to the Xception and Inception v4 models. Key performance metrics such as accuracy, Area Under the Curve (AUC), recall, and Harmonic Mean of Precision and Recall (F1 score) were used to evaluate its efficacy. Gradient-weighted Class Activation Mapping (Grad-CAM) heatmaps were utilized to provide interpretable visual evidence consistent with expert annotations.
RESULTS: The SE-Inception model demonstrated superior accuracy (93%) and AUC (94%), with high recall and F1 scores, indicating its efficacy in reducing false negatives and improving diagnostic reliability.
CONCLUSIONS: Despite the promising outcomes, the study acknowledges the limitation of dataset homogeneity and suggests further validation with diverse datasets for enhanced scalability. The findings support the inclusion of the SE-Inception model in clinical settings to improve diagnostic precision and patient care, particularly in nursing practices for effective pressure ulcer management.

Keywords: pressure ulcers; convolutional neural networks; Squeeze-and-Excitation; Grad-CAM; disease localization

Introduction

Overview of Pressure Ulcers

Pressure ulcers, known for their extensive prevalence, exhibit a marked variation across different countries [1]. In the US alone, hospitalizations related to pressure sores are estimated to be around 2.5 million annually [2]. A 2007 study recorded an average pressure ulcer prevalence of 18.1% across European hospitals [3]. In 2019, global data indicated 0.85 million decubitus cases with an age-standardized prevalence of 11.3 per 100,000, an incidence rate of 41.8 per 100,000, and years lived with disability (YLD) of 1.7 per 100,000 [4]. These statistics underscore the importance of understanding the global distribution of pressure ulcers to devise effective preventive strategies.

Pressure ulcers are primarily caused by prolonged pressure on the skin and are most prevalent among individuals with mobility issues, such as those bedridden, wheelchair-bound, or unable to shift their weight regularly [5,6]. Certain medical conditions, including stroke, spinal cord injury, and malnutrition, can also trigger the onset of pressure ulcers [7]. The severity of pressure ulcers can range from superficial redness to deep wounds that penetrate muscle and bone, necessitating treatments from simple repositioning to complex dressing changes and debridement.

Preventive and curative nursing interventions for pressure ulcers encompass diverse strategies to prevent skin breakdown and promote effective wound healing [8]. Common approaches involve regular patient repositioning, maintaining skin cleanliness and dryness, using specialized mattresses and cushions to alleviate pressure, assessing the skin for signs of redness or breakdown, and applying topical creams and dressings [9]. The severity-based classification of pressure ulcers assists in determining the most effective treatment plan [10]. Pressure ulcers are categorized into four stages, each indicating increasing severity: Stage I (superficial redness), Stage II (open wound with shallow crater), Stage III (deeper ulcers extending into the fat layer), and Stage IV (ulcers infiltrating muscle and bone with tissue loss and exposed bone) [11].

Pressure ulcers pose a significant challenge in clinical settings due to their high prevalence and severe complications if not promptly addressed. Early detection and accurate di-

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agnosis are crucial in preventing the progression of pressure ulcers and mitigating their impact on patient health. However, these tasks are challenging due to the subtle early signs that can be easily overlooked, leading to delayed treatment and worsening of the condition. Moreover, the subjective nature of visual assessments by healthcare providers often results in high misdiagnosis rates, complicating patient care. Therefore, there is a pressing need for more reliable and automated detection methods that can assist clinicians in identifying and diagnosing pressure ulcers accurately and efficiently.

Evolution of Automated Medical Image Analysis

The field of automated medical image analysis, characterized by the use of computer algorithms to scrutinize medical images, is advancing rapidly [12]. This technology can potentially transform medical diagnosis and treatment, enhancing accuracy and efficiency in disease detection and diagnosis [13]. In decubitus ulcer recognition, automated image analysis identifies skin abnormalities such as redness, discoloration, and open wounds, quantifies the size and shape of pressure ulcers, detects changes in tissue structure, and monitors disease progression [14,15]. The adoption of this technology empowers healthcare professionals to identify and diagnose pressure ulcers more quickly and accurately, facilitating earlier treatment and preventing severe health complications [16].

Medical Image Analysis Using Convolutional Neural Network (CNN)

This study proposes an innovative framework that integrates Squee-and-Excitation Network (SENet) with the Inception model, resulting in a custom Squeeze-and-Excitation (SE)-Inception model designed to improve the limitations of existing technologies such as Inception v4 and Xception.

Convolutional Neural Network (CNN) have emerged as powerful tools in the field of medical image analysis, offering enhanced capabilities for object detection, classification, and abnormality recognition in images, such as tumors, lesions, and organs [17,18]. Numerous studies highlight the effectiveness of Convolutional Neural Networks (CNNs), especially pre-trained models, in facilitating detailed and accurate analysis of medical images [19]. The diagnostic accuracy of deep learning in identifying pathologies from chest radiograph data has been explored, demonstrating its potential in automated and high-precision detection [20]. The feasibility of employing fine-tuned, pre-trained deep CNNs instead of training a deep CNN from scratch for medical image analysis has also been substantiated [21].

Advanced frameworks for Content-Based Medical Image Retrieval (CBMIR) Systems have leveraged deep CNN trained for medical image classification tasks [22]. The concept of a single CNN trained for multiple segmentation tasks has been explored, indicating potential efficiency gains [23]. Novel methodologies have been suggested, such as a two-stage task-oriented deep learning approach for real-time detection of large-scale anatomical landmarks, overcoming the challenges of limited medical data availability for network learning [24].

Innovative solutions, such as Shallow-Deep CNN (SD-CNN), create virtual compositions from limited energy images for classification tasks [25]. Synthetic medical images generated through deep learning Generative Adversarial Networks (GANs) have also shown promise, expanding the horizons of what's achievable in the field [26]. Attention-based CNN models, like Context-Aware Network (CA-Net), offer more precise and interpretable medical image segmentation by simultaneously considering key positional, channel, and scale parameters [27]. The use of Three-Dimensional (3D) CNNs for medical image analysis has been gaining traction, with comprehensive studies detailing the mathematical aspects and necessary preprocessing steps for medical images to be analyzed by 3D CNNs [28].

While previous studies have laid the foundation by employing CNNs for medical image recognition, this study aimed to refine the approach by integrating SENet with the Inception model to develop a system specifically optimized for detecting and characterizing pressure ulcers. The novelty of this research lies in the customized SE-Inception model, which is hypothesized to surpass the capabilities of established models like Inception v4 and Xception in recognizing subtle variations in ulcer presentations.

Crucial to this study is the classification accuracy and the interpretability of the results. By incorporating Gradient-weighted Class Activation Mapping (Grad-CAM) technology, the research introduces an advanced visual explanatory layer highlighting critical areas of interest in the images, providing clinicians with an intuitive heatmap of the ulcerated regions. This feature is expected to enhance diagnostic precision by revealing the specific location and extent of tissue damage, thus allowing medical professionals to understand the severity and progression of pressure ulcers rapidly.

Existing Technologies and their Limitations

Current technologies for pressure ulcer detection, including visual inspection, manual palpation, ultrasound, infrared thermography, and Magnetic Resonance Imaging (MRI), have significant limitations. Visual inspection and manual palpation are subjective and heavily rely on clinician experience, often resulting in inconsistent and delayed diagnoses. Ultrasound, although applicable, requires specialized equipment and training and is limited by penetration depth and resolution, making it impractical for routine use. Infrared thermography is sensitive to environmental conditions and patient movement, frequently leading to false positives. MRI, while providing detailed imaging, is costly and time-consuming, rendering it unsuitable for routine screening. These limitations highlight the need for more reliable, objective, and accessible diagnostic tools. The SE-Inception model aims to address these gaps by leveraging advanced deep learning techniques to enhance the accuracy and reliability of pressure ulcer detection, promising better patient outcomes and improved clinical management.

Materials and Methods

The Proposed System

To advance the diagnostic accuracy for pressure ulcers, our research proposed an integrated system employing a sophisticated ensemble of deep learning models enhanced by the explanatory power of Grad-CAM visualizations. The architecture of the proposed system unfolds through several stages, beginning with data preparation and culminating in the deployment of a diagnostic model, as illustrated in Fig. 1.

In this study, 1385 pressure ulcer images were gathered from a local hospital, each with a resolution of 1024×1024 pixels, tailored to the input resolution of our deep learning models. The dataset was categorized into four classes based on the severity of the pressure ulcers-Class I (585 cases), Class II (428 cases), Class III (232 cases), and Class IV (140 cases). The original images, initially sized at 1024×1024 pixels, were resized during the pre-processing stage to 225×225 pixels that better suited the model's requirements, as reflected in the scales used in Fig. 2. The dataset is methodically partitioned into distinct training and validation sets using an 80:20 ratio to ensure that the model has access to sufficient data for learning while retaining enough data for validation to reliably assess performance.

Given the imbalance in class distribution, majorly with fewer instances in Class III and IV, data augmentation techniques were extensively applied to the training set to artificially increase the number of samples and enhance the potential of the model to generalize across all classes. Techniques such as rotation, flipping, scaling, and adding Gaussian noise were employed to create a more balanced and diverse training dataset.

The pre-processing regimen involved a series of techniques designed to render the images more conducive for analysis. Adjustments to contrast and brightness are applied to accentuate ulcer features. Normalization was used to standardize pixel values to a uniform range, ensuring algorithmic stability during the learning process. Image cleaning is performed to remove irrelevant artifacts. Grayscale masks were applied to highlight ulcerated areas, providing the neural network with a clarified target for feature extraction. Additionally, Gaussian noise was introduced as a prophylactic measure against overfitting, improving the capacity of the model to generalize across unseen data.

To address the class imbalance within the dataset, extensive data augmentation was applied during the pre-processing stage. The augmentation techniques introduced various transformations to diversify the dataset with a range of ulcer presentations. These transformations encompassed rotations within a range of –15 to +15 degrees, horizontal and vertical flipping to simulate different viewpoints, scaling the images by a factor of 0.8 to 1.2, random translations shifting the images horizontally or vertically by up to 10% of the image dimensions, intensity scaling to simulate changes in lighting conditions, adding small amounts of Gaussian noise to make the model robust to noisy inputs, and applying random elastic deformations to mimic real-world distortions of the skin surface. These transformations were implemented using the Imgaug and Albumentations libraries, providing a comprehensive suite of data augmentation tools. Applying these techniques significantly diversified the training dataset, aiding the SE-Inception model in better generalizing to unseen data. Fig. 2 depicts a comparison between the original and pre-processed images.

During the training phase, the convolutional neural networks were configured and optimized. The Squeeze-and-Excitation Network (SENet) was seamlessly integrated with the spatially intelligent Inception model. Additionally, Inception v4 and Xception models were included to enrich the comparative analysis. These architectures were independently trained on the pre-processed images, with their hyperparameters optimized to achieve peak performance specific to pressure ulcer recognition.

In the evaluation phase, metrics such as accuracy, precision, recall, and the Harmonic Mean of Precision and Recall (F1 score) were computed to assess the diagnostic capabilities of the models. Furthermore, the integration of Grad-CAM technology generated heatmaps that highlighted critical regions indicative of ulceration, enhancing the interpretability of the model and providing medical practitioners with a visual exposition of the pathology.

The Integration of Squeeze-and-Excitation Networks with Inception

SENet, an architecture introduced by Hu *et al.* in 2018 [29], incorporates a recalibration mechanism to explicitly model the interdependencies between channels of convolutional features. SENet adjusts channel-wise feature responses adaptively, emphasizing informative features while suppressing less useful ones, thereby enhancing the representational power of the network. To complement the strengths of SENet, the Inception model [30] was leveraged, culminating in the SE-Inception model, as depicted in Fig. 3. The figure encapsulates the architectural synergy between the SENet and the Inception model, culminating in the SE-Inception model. The foundational Inception characteristic feature is shown in the left segment of Fig. 3, illustrating a direct mapping from the input image, denoted by X, through the Inception module to produce an output $\hat{X}$.

Enhancing this configuration, SENet was integrated into the model, initiating a novel recalibration of the convolutional

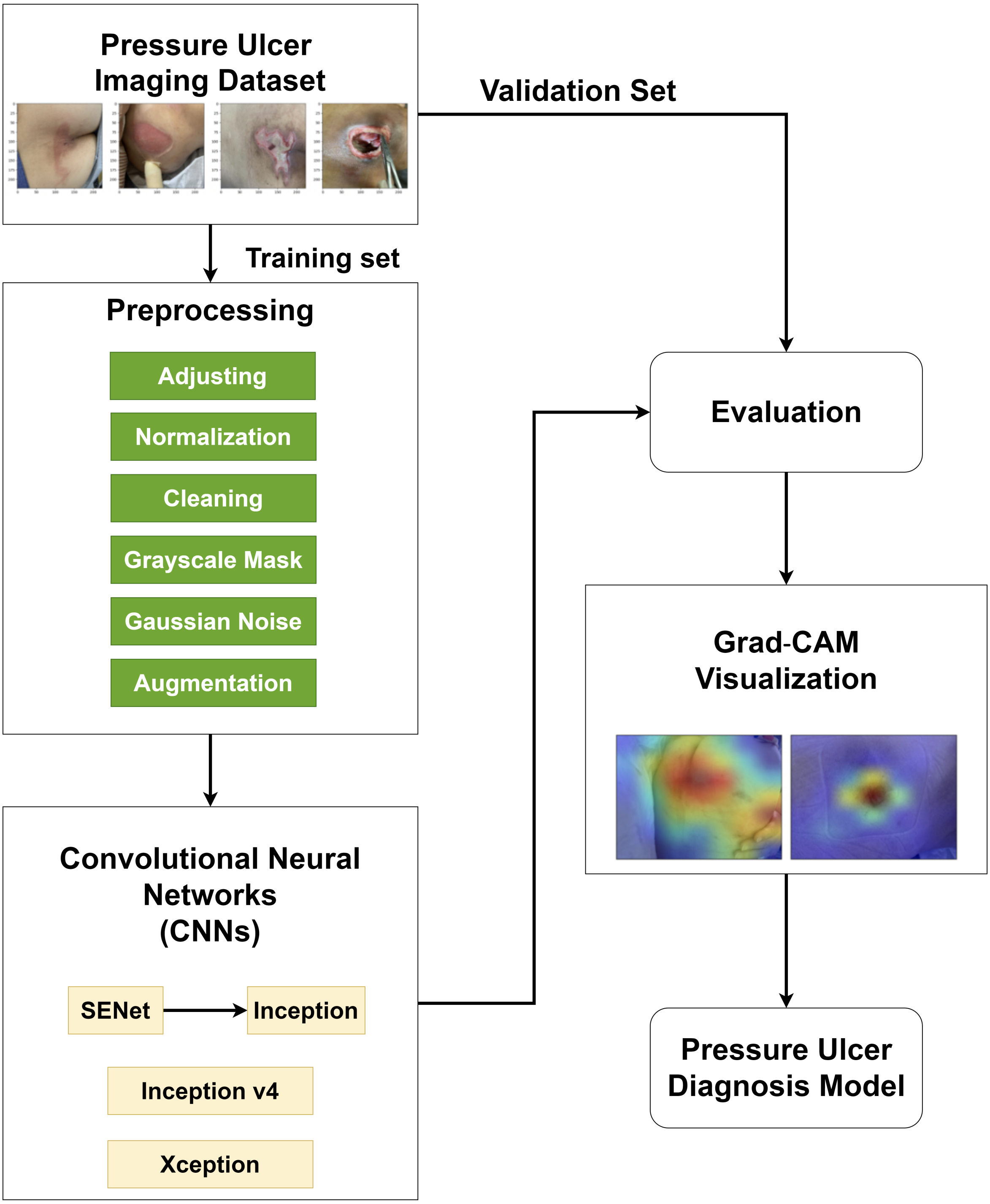

Fig. 1. Schematic diagram of the proposed deep learning-based system for pressure ulcer diagnosis. Grad-CAM, Gradient-weighted Class Activation Mapping; SENet, Squeeze-and-Excitation Network.

features output by the Inception module. This integration is illustrated in the right segment of Fig. 3, where the output of the Inception module, indicated as W × H × C (W, Width of the feature map; H, Height of the feature map; C, Number of channels in the feature map), transforms the SENet mechanism. The SENet mechanism commences with a global average pooling layer, reducing the spatial dimensions to 1 × 1 × C, thus condensing each channel into a single de-

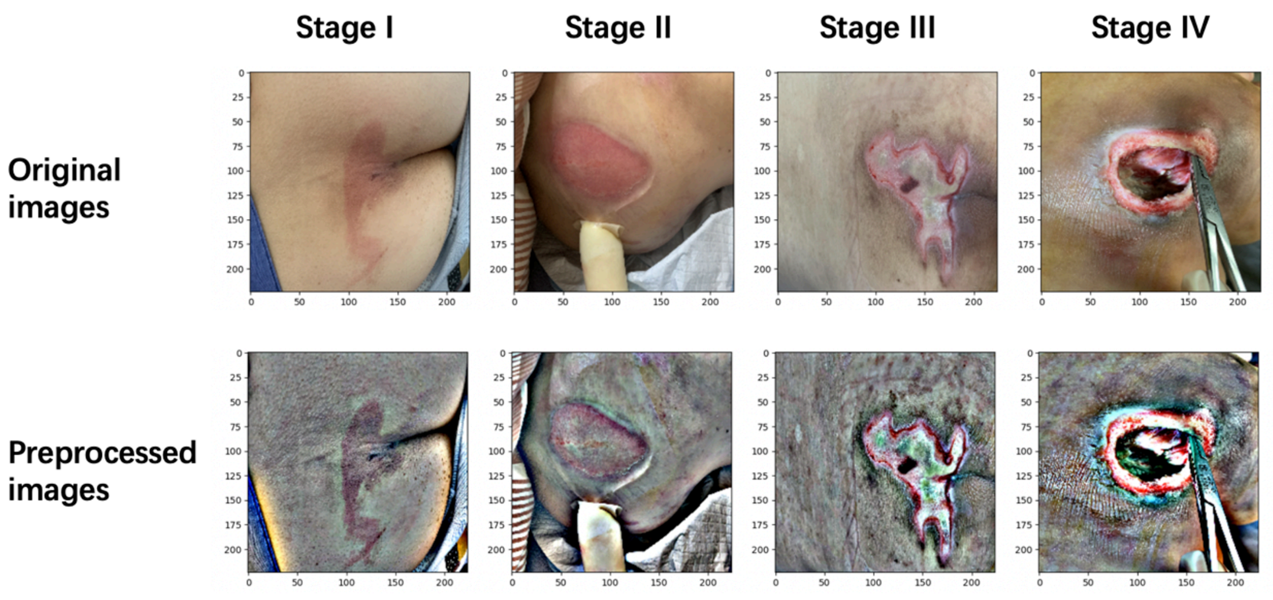

Fig. 2. Original and pre-processed pressure ulcer images.

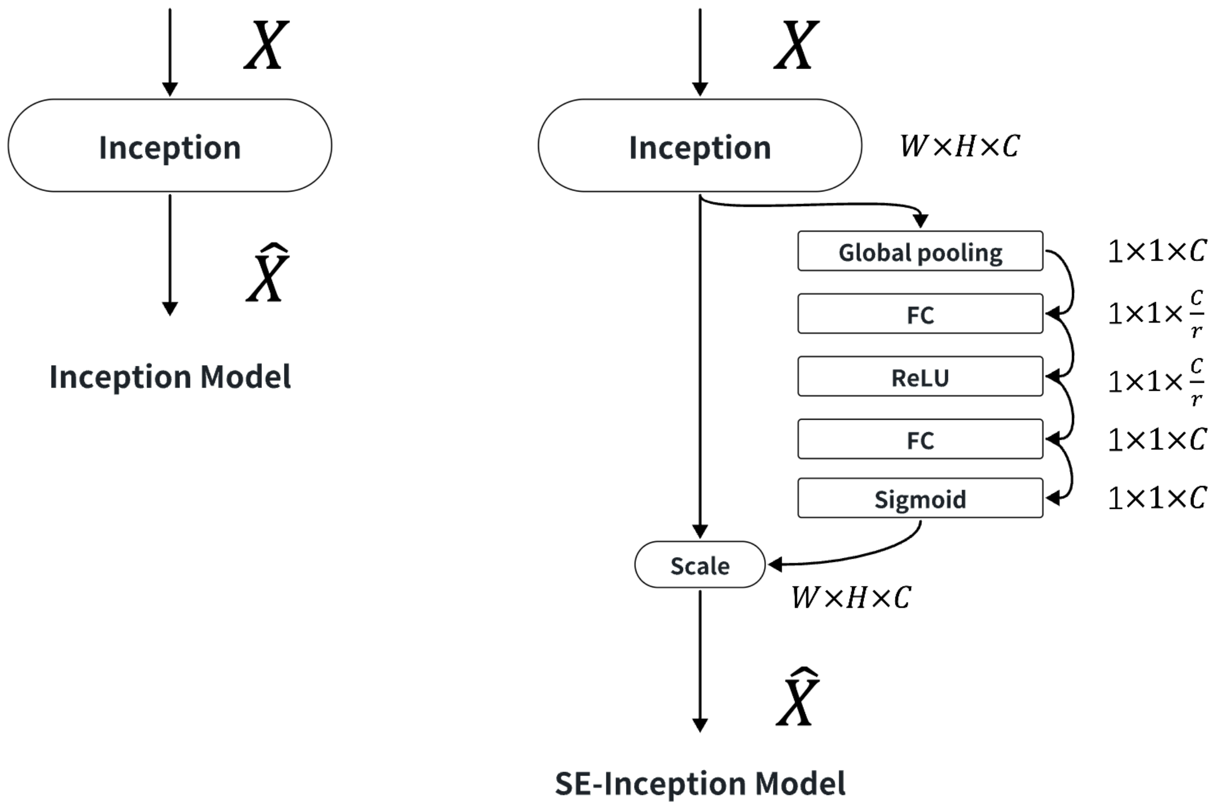

Fig. 3. Integration of Squeeze-and-Excitation (SE) blocks into the Inception model architecture. ReLU, Rectified Linear Unit; FC, fully connected; W, Width of the feature map; H, Height of the feature map; C, Number of channels in the feature map.

scriptor. A fully connected (FC) layer captured the channel-wise dependencies following the pooling layer. The number of neurons in this layer is a fraction of C, denoted by C/r, where r represents the reduction ratio, a hyperparameter determined empirically to balance complexity and efficacy.

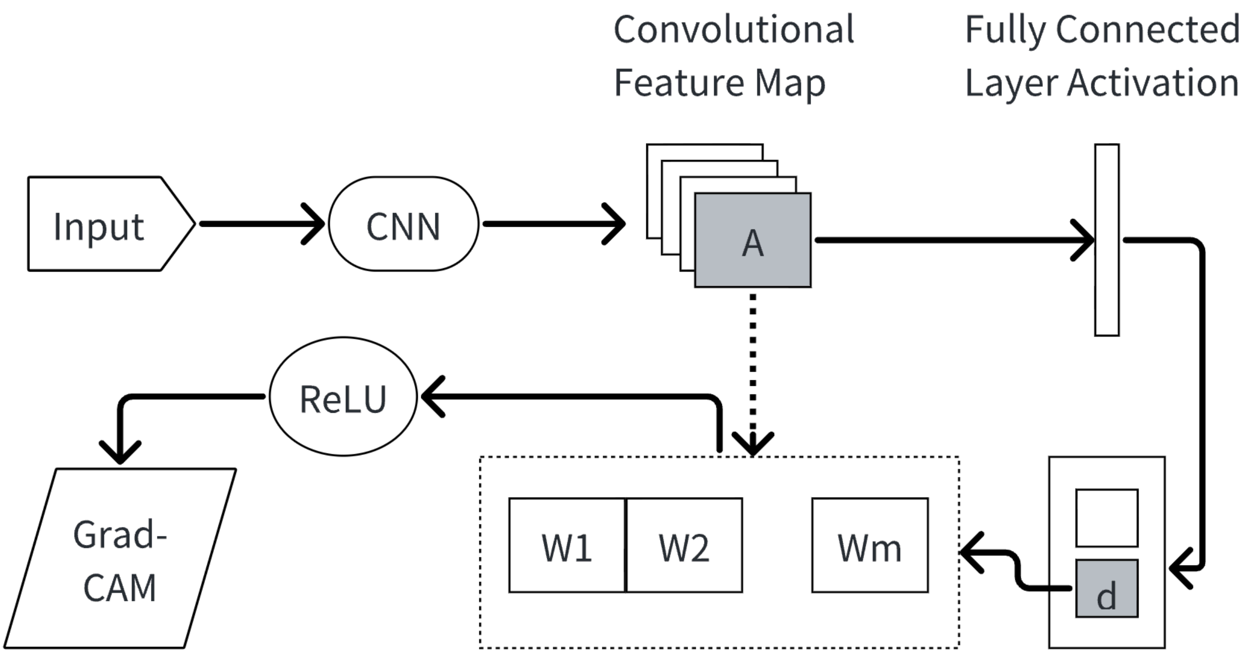

Fig. 4. Illustration of the Grad-CAM process with Squeeze-and-Excitation (SE)-Inception model. ReLU, Rectified Linear Unit; W, Weight; CNN, Convolutional Neural Network.

The Rectified Linear Unit (ReLU) activation function introduced non-linearity into the network after the first FC layer, enhancing the capability to model complex functions. A second FC layer then elevated the neuron count back to the original channel depth C, reconstructing the channel-wise statistics. Following the second FC layer, the sigmoid activation function generated a set of weights between 0 and 1 for each channel, enabling dynamic channel-wise feature recalibration.

The culmination of this sequential operation was the scaling step, where the learned channel-wise weights reweighted the original feature maps produced by the inception module. This process intricately modulated the significance of each channel based on the content of the input image, achieving the spatial recalibration characteristic of SENet.

Comparative Analysis of Adapted SE-Inception, Inception v4, and Xception

To contextualize the efficacy and performance of our SE-Inception model, established architectures such as Inception v4 [31] and Xception were employed for comparative analysis. The Inception v4 model, an evolution of its predecessors in the Inception lineage, was chosen for its sophisticated and structured design conducive to extracting high-level features from medical imagery. The Xception model, representing a modification and extension of the Inception architecture, replaces convolutional operations with depth-wise separable convolutions, thus intensifying the ability of the model to capture cross-channel correlations and feature mappings [32].

Inception v4 and Xception models were subjected to the same pre-processing techniques as the SE-Inception model. The models were trained using a robust dataset of pressure ulcer images, which were split into designated training and validation sets.

An extensive hyperparameter optimization process was undertaken to ensure that the SE-Inception model was aptly tuned for the specific task of pressure ulcer classification. The hyperparameters considered included learning rate, batch size, weight decay, and dropout rate. The tuning process employed a combination of grid search and random search methods to explore the hyperparameter space effectively. The learning rate was varied between 0.0001 and 0.01, with a finer grid search performed within this range to identify the optimal value that minimizes validation loss while ensuring stable convergence. Batch sizes of 16, 32, and 64 were tested, focusing on achieving a balance between efficient learning and computational feasibility. Weight decay values ranging from 0.0001 to 0.001 were examined to control overfitting by penalizing large weights during training. Dropout rates between 0.2 and 0.5 were tested to determine the optimal rate for regularization, aiming to improve the ability of the model to generalize to unseen data.

The selection criteria for the final hyperparameters were based on performance metrics obtained on the validation set, including accuracy, precision, recall, and F1 score. The combination of hyperparameters that yielded the highest F1 score on the validation set was chosen as the final configuration for the SE-Inception model. This approach ensured that the model achieved high accuracy and maintained a balance between precision and recall, which is crucial for effective pressure ulcer detection. The learning rate was set to initiate at 0.001, and the model underwent training for 20 epochs. The optimizer of choice was Adam, preferred for its adaptive learning rate capabilities, and was employed with beta1 and beta2 parameters set to 0.9 and 0.999, respectively, following the recommendations of Kingma and Ba in 2014 [33].

Integration of Grad-CAM Technology

In the subsequent phase of the research, critical to the enhancement of the utility of the SE-Inception model, Gradient-weighted Class Activation Mapping (Grad-CAM) technology was integrated. Grad-CAM employs the gradients of any target concept, flowing into the final convolutional layer to produce a coarse localization map highlighting the important regions in the image for predicting the concept [34]. By integrating Grad-CAM with the SE-Inception model, the research aimed to achieve high classification accuracy and achieve a level of interpretability quintessential for clinical diagnosis. Through this integration, the model produced heatmaps that were superimposed on the original medical images, thereby providing clinicians with an illustrative representation of the focus areas of the model during the diagnostic process.

In Fig. 4, Grad-CAM starts with an input image processed through the layers of a CNN, extracting complex patterns and features. These patterns are then abstracted into a convolutional feature map, labeled 'A'. As these features transition through the network, they activate various neurons in the fully connected layers, leading to a decision. By computing the weights for the importance of each neuron (Weight (W)1 to Wm) through global average pooling of the gradients, Grad-CAM provides a localization map that underscores the pertinent regions in the image. The subsequent step involves applying a ReLU function to the weighted combination of feature maps, ensuring that only the features positively influencing the target prediction are visualized. This results in a heatmap that mirrors the size of the convolutional feature maps, emphasizing the critical areas for the prediction of CNN.

Results

The empirical evaluation of the proposed SE-Inception model was meticulously performed and compared with the established Xception and Inception v4 models. The results, graphically depicted in Fig. 5a,b, indicate the progression of model accuracy over training epochs and the comparative analysis of performance metrics, respectively.

Fig. 5a illustrates the training accuracy of the three models as a function of epochs. The accuracy trajectory of the SE-Inception model was observed to ascend in a fashion akin to the Xception and Inception v4 models, yet it demonstrated a distinct improvement in the stabilization of accuracy over epochs. The gradual rise in accuracy for the SE-Inception model highlighted its efficient learning capability and generalization over the training data. Notably, while the Xception and Inception v4 models experienced slight fluctuations in accuracy beyond the 10th epoch, the SE-Inception model maintained a consistent improvement, showcasing its robustness in learning from the dataset.

Following the training phase, the performances of the models were evaluated based on standard metrics: Accuracy, Area Under the Curve (AUC), Recall, and F1 Score, as presented in Fig. 5b. The SE-Inception model surpassed the Xception and Inception v4 models in all evaluated metrics. The SE-Inception model exhibited the highest accuracy (93%), indicating its superior predictive performance in classifying pressure ulcers from medical images. In terms of AUC, a metric that reflects the ability of the model to distinguish between classes, the SE-Inception model marginally outperformed others with a score of 94%, reinforcing its efficacy in detection tasks.

The recall metric, which measures the capability of the model to identify all relevant instances, was notably higher for the SE-Inception model, suggesting its proficiency in minimizing false negatives, a crucial aspect in medical diagnostics. Moreover, the F1 Score, a harmonic mean of precision and recall, was the highest for the SE-Inception model (93%), highlighting its balanced classification capacity, especially in a medical setting where false positives and false negatives carry significant consequences.

The results cumulatively indicated that integrating Squeeze-and-Excitation blocks within the Inception architecture significantly enhanced the ability of the model to identify and characterize nuances in pressure ulcer images. The superior performance of the SE-Inception model was attributed to its capability to dynamically recalibrate feature responses, emphasizing informative features while suppressing less useful ones.

In this study, an examination of Grad-CAM heatmaps was conducted to evaluate the performance of the SE-Inception model across different stages of pressure ulcer progression. The dataset comprised pressure ulcer images grouped into four stages, from Stage I to Stage IV, each representing increasing severity. For each original image, a heatmap was generated using the Grad-CAM algorithm to indicate the regions of the highest significance according to the classification of the SE-Inception model. Dermatology experts were then enlisted to independently identify and distinguish the affected areas on the original images. The expert analysis served as a reference standard to assess the focus of the accuracy of the model as depicted by the heatmaps.

As shown in Fig. 6, the alignment between the highlighted regions in the Grad-CAM heatmaps and the annotations by the experts was notably evident. The heatmaps accurately reflected the gradation of severity, with the intensity and spread of the highlighted regions increasing from Stage I to Stage IV. The visual analysis underscored the capabil-

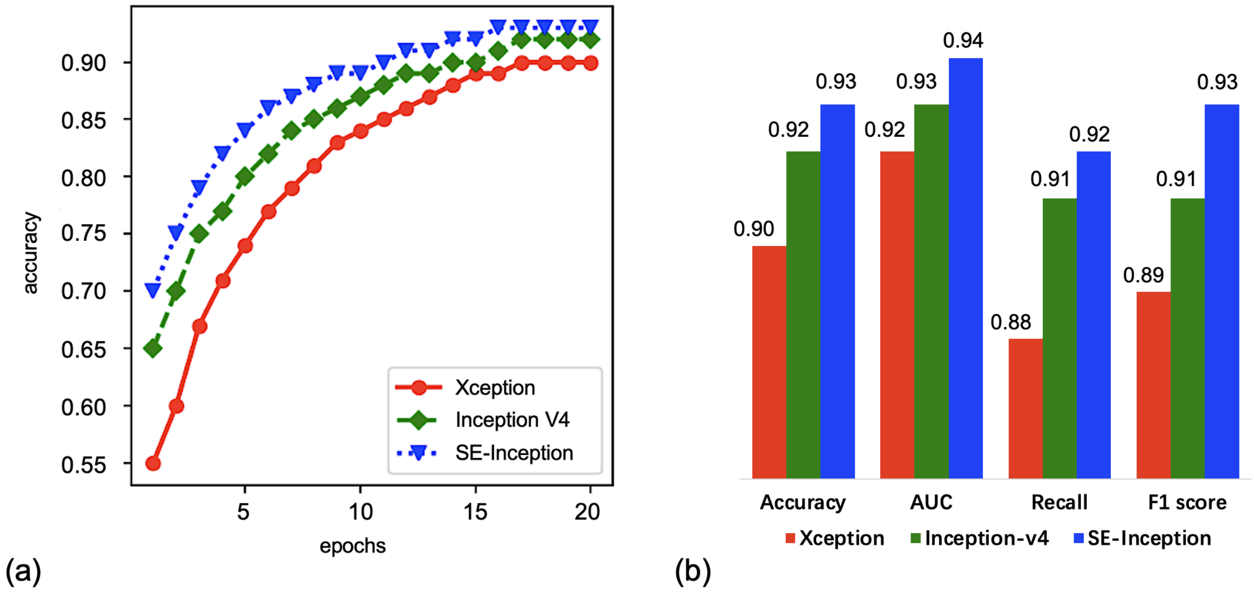

Fig. 5. Comparative performance evaluation of deep learning models for pressure ulcer classification. (a) Training Accuracy of Models. (b) Performance Evaluation Metrics. AUC, Area Under the Curve; F1 score, Harmonic Mean of Precision and Recall.

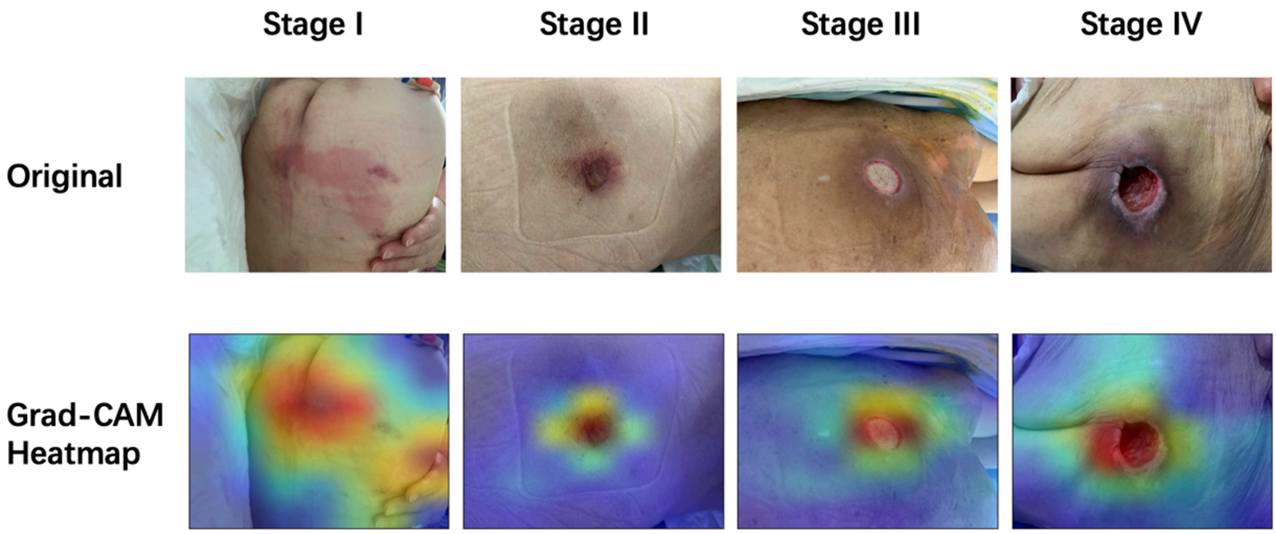

Fig. 6. Visualization of pressure ulcer stages and corresponding Grad-CAM heatmaps.

ity of the SE-Inception model to classify pressure ulcers accurately and to localize the affected tissue with remarkable precision. For Stage I ulcers, the heatmap revealed a concentrated focus on mild discolorations and initial tissue damage. As the severity escalated to Stages II and III, the Grad-CAM visualizations expanded, corresponding to increased tissue damage and ulceration. In Stage IV, the heatmaps precisely delineated the extensive tissue necrosis and deep ulceration, mirroring the clinical features of advanced pressure ulcers.

The concurrence between the Grad-CAM heatmaps and expert annotations confirmed the robustness of the SE-Inception model in identifying the salient features within the images. These findings suggest that integrating Grad-CAM with the SE-Inception model enhances the classification performance and provides a transparent diagnostic tool, enabling clinicians to visualize and verify the areas identified by the model as indicative of pressure ulcers.

Discussion

The exploratory analysis of the SE-Inception model has demonstrated a significant advancement in medical image analysis, particularly in pressure ulcer classification. The comparative study indicated that the SE-Inception model excelled in key performance metrics over its predecessors, the Xception and Inception v4 models. Achieving an accuracy of 93% and an AUC of 94%, the SE-Inception model exhibited a remarkable ability to effectively distinguish between classes of pressure ulcers [35].

One of the primary reasons for the superior performance of the SE-Inception model is the inclusion of SE blocks, which provide a mechanism for adaptively recalibrating channel-wise feature responses by explicitly modelling interdependencies between channels. These blocks employ a self-gating mechanism that dynamically learns to emphasize informative features while suppressing less applicable ones [29]. This mechanism is crucial in medical image analysis, where distinctions between classes, such as different stages of pressure ulcers, can be subtle and highly nuanced.

Moreover, the SE-Inception model benefits from depth-wise separable convolutions, as utilized in the Xception architecture, allowing for the separation of learning spatial hierarchies and channel-wise correlations in image data. This increases the ability of the model to abstract features from medical images, where precision is paramount. In contrast to traditional convolutional networks, which may not capture such complex features as effectively, the approach of the SE-Inception model enables more sophisticated pattern recognition, potentially reducing false positives and false negatives in pressure ulcer classification.

Grad-CAM heatmaps are pivotal in providing visual explanations for the predictions of the model, enhancing trust in AI-assisted diagnostics among medical professionals [34]. This visual congruence with expert opinion reinforces confidence in the diagnostic decisions of the model and serves as a stepping stone toward explainable AI in healthcare.

The SE-Inception model, with its enhanced diagnostic accuracy and robustness, holds significant potential for various clinical applications. In hospital settings, it can be used for early detection of pressure ulcers in patients with limited mobility, leading to timely interventions and preventing progression to severe stages, thus improving patient outcomes and reducing costs. Telemedicine facilitates remote diagnosis, particularly benefiting patients in underserved areas by enabling prompt medical advice and intervention. In long-term care facilities, the model assists nursing staff by providing automated and accurate assessments, reducing workload and human error, and leading to better preventive care and enhanced quality of life for residents.

The improved diagnostic accuracy directly impacts patient outcomes by reducing misdiagnosis, enhancing treatment efficacy, and lowering healthcare costs. With higher accuracy and recall rates, the SE-Inception model minimizes the chances of false positives and false negatives, ensuring appropriate and timely treatment for patients. Early and accurate pressure ulcer allows for targeted treatments that improve healing rates and reduce complications. The integration of Grad-CAM technology provides interpretability, enhancing confidence in the AI system and aiding clinical decision-making.

In summary, the superior performance and explainability of the SE-Inception model make it a valuable tool in various clinical settings, potentially leading to improved patient outcomes, more efficient use of healthcare resources, and enhanced overall quality of care.

Integrating the SE-Inception model into nursing practices significantly advances pressure ulcer management. Nurses are crucial in preventing and treating pressure ulcers, making their involvement essential in applying new technologies. The SE-Inception model, with its high diagnostic accuracy and interpretability through Grad-CAM heatmaps, provides nurses with a valuable tool for early detection and assessment of pressure ulcers.

Incorporating this technology into daily nursing care can enhance the effectiveness of preventive measures, such as patient repositioning and skin assessments, by identifying at-risk areas before visible symptoms appear. It can also aid in the accurate staging of existing ulcers, enabling nurses to effectively tailor treatment plans and monitor healing progress with greater precision.

To fully realize the benefits of the SE-Inception model, nursing education programs should include training on interpreting its outputs and integrating these insights into patient care plans. This approach promotes a collaborative environment where technology and traditional nursing care converge to improve patient outcomes in pressure ulcer management.

The limitations of this study must be comprehensively addressed to understand the potential biases introduced by the homogenous dataset and their impact on the generalizability of the findings. Using a homogenous dataset limits the exposure of the model to diverse patient demographics, potentially leading to overfitting and biased performance when applied to broader populations. This limitation may result in reduced accuracy and reliability of the model in different clinical settings, especially those involving varied ethnic and demographic groups.

However, our study is not without its limitations. The training and validation of the model were performed on a dataset sourced from a homogenous population. Using a homogenous dataset limits the exposure of the model to diverse patient demographics, potentially leading to overfitting and biased performance when applied to broader populations. To ensure the scalability and applicability of the model in diverse clinical settings, it is imperative to train and validate the model using data encompassing a wider demographic and ethnic diversity [36].

Future research should incorporate more diverse datasets that reflect a wider range of patient characteristics, including different ages, ethnicities, and medical conditions to mitigate these biases and enhance the generalizability of the model. Additionally, implementing cross-validation techniques and external validation with independent datasets can offer a more robust assessment of the performance of the model across various clinical environments.

Future research should include multi-center studies involving diverse geographic locations and healthcare institutions to validate the applicability of the SE-Inception model across different clinical settings. This approach ensures that the model performs well under various conditions and with different patient populations, enhancing its robustness and reliability. Integrating additional types of medical images, such as CT, MRI, and ultrasound, can further validate the versatility of the model and expand its application to other medical imaging domains. Investigations into the interpretability of the model by end-users and its integration into clinical decision-support systems are necessary to realize its full potential in a real-world healthcare environment [37]. Moreover, exploring the use of data augmentation techniques and synthetic data generation can help address the limitations of small or imbalanced datasets, improving the performance and generalizability of the model. Evaluating the real-world performance of the model through prospective clinical trials and its integration into existing clinical workflows will provide valuable insights into its practical utility and impact on patient outcomes.

Conclusions

In summary, the SE-Inception model performs better in the classification of pressure ulcers, surpassing previous models such as Xception and Inception v4. Integrating Squeeze-and-Excitation blocks has notably enhanced its ability to focus on the most relevant features in medical images, a critical aspect in the precise classification of medical conditions. Grad-CAM heatmaps offer a transparent view into the decision-making process of the model, enhancing its acceptance in clinical practice. However, additional studies across more diverse datasets are essential to establish its efficacy universally. The promising results of this study indicate that the SE-Inception model represents a significant step towards advanced, interpretable AI in healthcare, with the potential to improve diagnostic accuracy and patient outcomes.

Availability of Data and Materials

Data available on request from the authors.

Author Contributions

ZYG, FFZ designed the research study. ZYG and JNW performed the research. JNW and YFF contributed to data acquisition and drafted the initial manuscript, and critically reviewed it for important intellectual content. GSG contributed to the validation of deep learning models. FFZ supervised the entire study, provided crucial feedback. All authors revised the manuscript critically for important intellectual content. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The ethical considerations pertaining to this research have been rigorously examined and approved by the Ethics Committee of Ningbo No.2 Hospital (No.YJ-NBEY-KY-2023-091-01). The study involving the utilization of medical images and data adheres to the highest standards of ethical conduct and patient confidentiality. The approval from the Ethics Committee underscores our commitment to upholding the welfare and rights of all individuals involved in this study. We hereby declare that informed consent was obtained from the human subjects involved in this study for the publication of their images. The purpose and nature of the study, as well as the potential risks and benefits, were explained to the participants prior to obtaining their consent. This study was in accordance with the Declaration of Helsinki.

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Conflict of Interest

The authors declare no conflict of interest.

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