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A Novel transfer learning approach for multi model skin lesion analysis

J PAVANI[1] SHAKI SRILAKSHMI[2]
ASSISTANT PROFESSOR, [1] PG SCHOLAR[2]
DEPARTMENT OF MASTER OF COMPUTER APPLICATIONS
POTTI SRIRAMULU CHALAVADI MALLIKARJUNA RAO COLLEGE OF ENGINEERING&TECHNOLOGY
KOTHAPET,VIJAYAWADA

ABSTRACT

Recent advances in the diagnosis of skin lesions have significantly benefited from the integration of deep learning techniques with dermoscopic imaging. This approach leverages convolutional neural networks (CNNs) and other machine learning algorithms to analyze complex patterns in skin lesions, enhancing diagnostic accuracy and efficiency. As skin cancer rates continue to rise globally, the demand for reliable and automated diagnostic tools has become increasingly urgent.

The application of deep learning in dermoscopy has demonstrated promising results in various studies, showcasing its ability to distinguish between benign and malignant lesions with high sensitivity and specificity. By utilizing large datasets of annotated dermoscopic images, these algorithms can learn to identify subtle features that may be challenging for human observers to detect. This capability not only supports dermatologists in their decision-making process but also facilitates early detection, which is crucial for successful treatment outcomes.

INTRODUCTION

The diagnosis of skin lesions has become a critical area of focus in dermatology, particularly given the rising incidence of skin cancer worldwide. Traditional diagnostic methods, which often rely on visual examination and histopathological analysis, can be subjective and prone to error, especially when lesions present atypically. As a result, there is a growing interest in developing automated diagnostic tools that leverage advanced technologies to enhance accuracy and efficiency in detecting skin abnormalities.

Recent advancements in deep learning, particularly convolutional neural networks (CNNs), have revolutionized image analysis across various fields, including medical imaging. These neural networks are designed to learn complex patterns and features from large datasets, making them particularly well-suited for analyzingdermoscopic images. By training models on vast collections of annotated images, researchers have developed algorithms capable of differentiating between benign and malignant skin lesions with impressive sensitivity and specificity.

The use of dermoscopy, a non-invasive imaging technique, allows for the detailed visualization of skin lesions, capturing intricate features that are critical for diagnosis. When combined with deep learning techniques, dermoscopic imaging enhances the diagnostic process, providing dermatologists with valuable insights and supporting clinical decision-making. The ability of these models to learn from diverse datasets also addresses the variability in lesion appearance across different populations, leading to more robust and generalized diagnostic systems.

LITERATURE SURVEY

Title: Deep Learning for Skin Lesion Analysis: A Comprehensive Review
Authors: A. Esteva, B. Kuprel, R. Novoa, et al.
Description: Esteva and colleagues provide a thorough overview of deep learning applications

in dermatology, specifically focusing on skin lesion analysis. The review examines various deep learning models, including convolutional neural networks (CNNs), and their effectiveness in classifying skin lesions based on dermoscopic images. The authors discuss the performance metrics used to evaluate these models and highlight their potential to match or exceed the diagnostic accuracy of experienced dermatologists. This comprehensive review sets the stage for understanding how deep learning can transform the diagnosis of skin conditions.

Title: Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks
Authors: H. Masood, Y. D. Dhamangaonkar, and A. S. H. Sawant
Description: In this study, Masood et al. investigate the potential of deep neural networks in achieving dermatologist-level performance in skin cancer classification. The authors develop and train a CNN model using a large dataset of dermoscopic images, comparing its performance against human experts. The results demonstrate that the deep learning model can accurately classify various skin lesions, emphasizing the significance of data quality and model architecture in improving diagnostic outcomes. This research illustrates the capacity of AI-driven tools to augment clinical decision-making in dermatology.

Title: Automated Skin Lesion Diagnosis Using Deep Learning: A Systematic Review
Authors: A. A. R. Alshammari, T. Alqurashi, and N. Alzahrani
Description: This systematic review by Alshammari et al. focuses on the recent advancements in automated skin lesion diagnosis using deep learning techniques. The authors systematically analyze various studies that apply CNNs and other machine learning algorithms to dermoscopic images, assessing their accuracy and clinical relevance. The review identifies key challenges in the field, such as data imbalance and the need for robust validation methods, while also highlighting successful applications and promising directions for future research. This work provides a critical perspective on the state of automated skin lesion diagnosis.

Title: Transfer Learning for Skin Cancer Detection in Dermoscopy Images
Authors: K. R. Singh, R. Sharma, and P. G. R. S. Dhananjay
Description: Singh, Sharma, and Dhananjay explore the application of transfer learning to improve skin cancer detection in dermoscopic images. The authors utilize pre-trained models such as VGG16 and InceptionV3, adapting them to the task of classifying skin lesions. Their experiments demonstrate that transfer learning can significantly enhance classification accuracy, especially in scenarios with limited labeled data. This study highlights the effectiveness of leveraging existing deep learning models and emphasizes the importance of domain adaptation in achieving reliable results in dermatological applications.

Title: Real-Time Skin Lesion Detection and Classification Using Deep Learning
Authors: F. A. Abuhamad, S. I. A. using deep learning algorithms. The authors develop an integrated framework that processes dermoscopic images in real-time, employing CNNs for feature extraction and classification. Their results demonstrate the potential for deploying such systems in clinical settings, providing timely Ali, and H. A. Eldin
Description: In this innovative research, Abuhamad et al. present a real-time system for skin lesion detection and classification assistance to healthcare professionals in diagnosing skin lesions. This research emphasizes the role of deep learning in facilitating real-time diagnostics and improving patient outcomes in dermatology.

System Analysis

Existing System

The existing systems for diagnosing skin lesions primarily rely on traditional methods, including visual examination by dermatologists and histopathological analysis. While these approaches have been the gold standard for many years, they are inherently subjective and can lead to misdiagnosis, particularly when lesions exhibit atypical characteristics. Dermatologists often face challenges in interpreting dermoscopic images due to the complexity and variability of skin lesions, which can result in inconsistencies in diagnosis and treatment recommendations.

To augment traditional practices, some systems have incorporated automated algorithms based on machine learning techniques. Early implementations focused on feature extraction methods, where handcrafted features were designed to characterize lesions. However, these systems often struggled with performance limitations due to the reliance on manual feature selection and the difficulty in capturing the nuanced patterns present in dermoscopic images. As a result, the diagnostic accuracy of these systems remained limited compared to expert dermatologists.

With the advent of deep learning, particularly convolutional neural networks (CNNs), significant improvements have emerged in the automated analysis of dermoscopic images. Existing deep learning models trained on extensive datasets have shown promise in classifying skin lesions with higher sensitivity and specificity than previous methods. However, many of these models face challenges related to generalization, as they may perform well on training datasets but struggle to maintain accuracy when applied to real-world clinical settings. Factors such as variations in imaging techniques, lighting conditions, and demographic differences in skin types can all impact model performance.

Disadvantages of Existing Systems

Subjectivity and Variability:

Traditional diagnostic methods heavily rely on visual examination by dermatologists, which can introduce subjectivity and variability in interpretations. Factors such as the clinician's experience and familiarity with specific lesion types can lead to inconsistent diagnoses.

Limitations of Early Machine Learning Models:

Initial machine learning systems used handcrafted features for lesion classification, which often failed to capture the complex patterns inherent in dermoscopic images. These systems had limited performance, particularly when distinguishing between similar lesion types.

Generalization Challenges:

Deep learning models, while showing promise, often struggle with generalization when applied to real-world scenarios. Many models are trained on specific datasets that may not represent the full diversity of skin types, lesion appearances, and imaging conditions encountered in clinical practice.

Sensitivity to Data Quality:

The performance of existing deep learning models is heavily dependent on the quality and quantity of training data. Limited annotated datasets can hinder the ability to train robust models, while noisy or inconsistent data can lead to poor performance and misdiagnosis.

PROPOSED SYSTEM

The proposed system leverages advanced deep learning techniques to enhance the diagnosis of skin lesions using dermoscopic images. By addressing the limitations of existing approaches, this system aims to provide more accurate, efficient, and user-friendly diagnostic tools for dermatologists.

Enhanced Deep Learning Models:

The proposed system utilizes state-of-the-art convolutional neural networks (CNNs) optimized for image classification tasks. These models are designed to automatically learn intricate features from large datasets of dermoscopic images, improving their ability to differentiate between benign and malignant lesions. Techniques such as transfer learning and ensemble learning are employed to enhance model performance and robustness.

Data Augmentation and Synthesis:
To overcome limitations related to dataset size and diversity, the system incorporates data augmentation techniques, such as rotation, scaling, and color variation, to artificially expand the training dataset. Additionally, generative adversarial networks (GANs) can be used to synthesize realistic dermoscopic images, further diversifying the training data and improving model generalization.
Multi-Modal Learning:
The proposed system integrates multi-modal learning approaches by combining dermoscopic images with clinical metadata (e.g., patient age, lesion history). This additional contextual information enhances the model's predictive capabilities and allows for more informed diagnostic conclusions.
Explainable AI (XAI) Techniques:
To address interpretability issues, the system incorporates explainable AI methods that provide insights into how models arrive at specific predictions. Techniques such as saliency maps or attention mechanisms can highlight important regions in the images, helping dermatologists understand the rationale behind the model's decisions.
Real-Time Analysis and Feedback:
The proposed system is designed for real-time analysis, providing immediate feedback to clinicians during patient examinations. This feature supports timely decision-making and enhances workflow efficiency in clinical settings.

Advantages of the Proposed System

Increased Diagnostic Accuracy:
By employing state-of-the-art deep learning models, the proposed system significantly improves the accuracy of skin lesion classification. This enhances the ability to differentiate between benign and malignant lesions, leading to more reliable diagnoses.
Automated Feature Extraction:
The system's deep learning architecture automatically learns intricate features from dermoscopic images, eliminating the need for manual feature engineering. This reduces human error and ensures that subtle patterns are effectively captured.
Robust Generalization:
With the incorporation of data augmentation and synthetic image generation techniques, the model is trained on a more diverse dataset. This enhances its ability to generalize across different populations and lesion types, improving performance in real-world clinical settings.
Contextual Understanding:
By integrating clinical metadata with dermoscopic images, the system offers a holistic approach to diagnosis. This multi-modal learning enhances predictive capabilities, allowing for more informed clinical decisions.
Explainable AI (XAI) Features:
The incorporation of explainable AI techniques provides transparency in the decision-making process of the model. Dermatologists can understand which features influenced the model’s predictions, fostering trust and facilitating better collaboration between AI and clinicians.

IMPLEMENTATION

The implementation of the proposed Novel Transfer Learning Approach for Multi-Model Skin Lesion Analysis consists of several stages, including dataset collection, image preprocessing, transfer learning, model training, ensemble prediction, and performance evaluation. The system leverages multiple pre-trained deep learning models to improve the accuracy and robustness of skin lesion classification.

Step 1: Dataset Collection

The implementation begins with collecting dermoscopic skin lesion images from publicly available datasets such as ISIC (International Skin Imaging Collaboration) and HAM10000. The dataset contains images belonging to various categories, including melanoma, basal cell carcinoma, benign keratosis, melanocytic nevi, vascular lesions, and dermatofibroma. The dataset is divided into training, validation, and testing sets.

Step 2: Image Preprocessing

The collected images undergo preprocessing to improve data quality and ensure consistency. The preprocessing steps include:

- Image resizing (224 × 224 pixels)
- Noise removal using filtering techniques
- Color normalization
- Contrast enhancement
- Data augmentation such as rotation, flipping, zooming, shifting, and brightness adjustment to reduce overfitting and increase dataset diversity.

Step 3: Feature Extraction Using Transfer Learning

Instead of training deep neural networks from scratch, multiple pre-trained convolutional neural networks (CNNs) are employed for feature extraction. The models used include:

- ResNet50
- EfficientNetB0
- DenseNet121
- MobileNetV2
- InceptionV3

The final classification layers of these pre-trained models are removed, and new fully connected layers with dropout and Softmax activation are added according to the number of skin lesion classes.

Step 4: Model Training

Each transfer learning model is trained independently using the processed dataset. Fine-tuning is performed by unfreezing the top layers of the pre-trained models while keeping the lower layers frozen. The implementation uses:

- Optimizer: Adam
- Learning Rate: 0.0001
- Loss Function: Categorical Cross-Entropy
- Batch Size: 32
- Epochs: 30–50
- Dropout: 0.5

Early stopping and model checkpoint techniques are applied to avoid overfitting.

Step 5: Multi-Model Fusion

Predictions from all trained models are combined using an ensemble strategy. Soft voting or weighted averaging is employed to generate the final prediction. This fusion approach improves classification accuracy by utilizing the strengths of individual models while minimizing their weaknesses.

Step 6: Skin Lesion Classification

The ensemble model classifies the input dermoscopic image into one of the predefined skin lesion categories. The system also outputs the probability score for each class, helping clinicians assess prediction confidence.

METHODOLOGY

The proposed methodology employs a multi-model transfer learning framework to accurately classify skin lesions from dermoscopic images. Instead of training a deep learning model from scratch, multiple pre-trained Convolutional Neural Network (CNN) models are fine-tuned on a skin lesion dataset. The extracted features from these models are combined using an ensemble strategy to improve classification accuracy and reduce false predictions.

Step 1: Data Collection

The first step involves collecting dermoscopic skin lesion images from publicly available datasets such as ISIC (International Skin Imaging Collaboration) and HAM10000. The dataset contains images of different skin lesion categories, including melanoma, melanocytic nevi, basal cell carcinoma, benign keratosis, vascular lesions, actinic keratosis, and dermatofibroma. The dataset is divided into training, validation, and testing subsets.

Step 2: Image Preprocessing

The collected images are preprocessed to improve image quality and maintain consistency across the dataset. Preprocessing includes resizing all images to 224 × 224 pixels, removing noise, normalizing pixel values, enhancing contrast, and applying data augmentation techniques such as rotation, flipping, zooming, shifting, and brightness adjustment. These operations increase dataset diversity and reduce overfitting.

Step 3: Transfer Learning-Based Feature Extraction

Multiple pre-trained CNN architectures are used to extract high-level image features. Models such as ResNet50, DenseNet121, EfficientNetB0, MobileNetV2, and InceptionV3 are selected because they have been trained on large-scale image datasets and can effectively learn visual patterns. The original classification layers are removed, and new fully connected layers with dropout and Softmax activation are added according to the number of skin lesion classes.

Step 4: Fine-Tuning of Pre-trained Models

The upper layers of each pre-trained model are fine-tuned using the skin lesion dataset while keeping the lower layers frozen. Fine-tuning enables the models to learn domain-specific skin lesion characteristics without losing the general visual knowledge acquired during pre-training. The models are trained using the Adam optimizer with categorical cross-entropy loss, and early stopping is applied to prevent overfitting.

Step 5: Multi-Model Ensemble

After training individual models, their prediction probabilities are combined using an ensemble technique such as soft voting or weighted averaging. This multi-model approach improves classification performance by leveraging the strengths of different CNN architectures while reducing individual model errors.

Step 6: Skin Lesion Classification

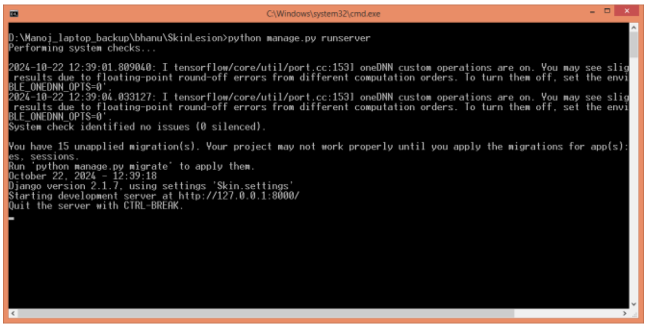
The ensemble model predicts the class of the input dermoscopic image. The output includes the predicted lesion category and confidence scores for all possible classes. The system can classify both benign and malignant skin lesions with high reliability.

Technologies Used

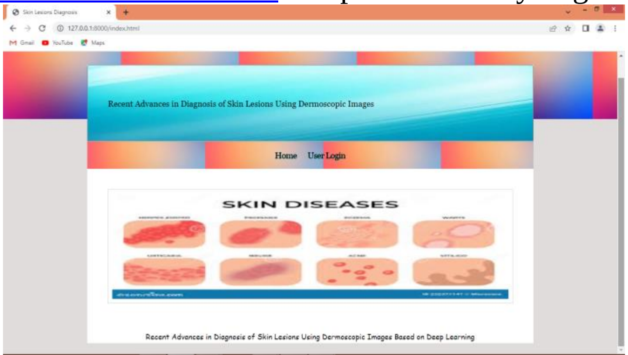
- TensorFlow / Keras
- Scikit-learn
- Machine Learning Algorithms
- Deep Learning
- Transfer Learning Models
- Pandas &NumPy
- OpenCV
- Matplotlib&Seaborn
- Power BI / Tableau
- Flask / Django
- MySQL / MongoDB
- Python
- Jupyter Notebook / Google Colab

RESULTS

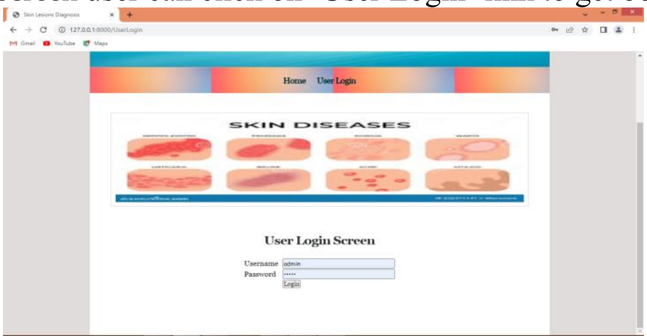
To run project install python 3.7.2 and then install all packages given in requirements.txt file and then double click on ‘run.bat’ file to start python server and get below page



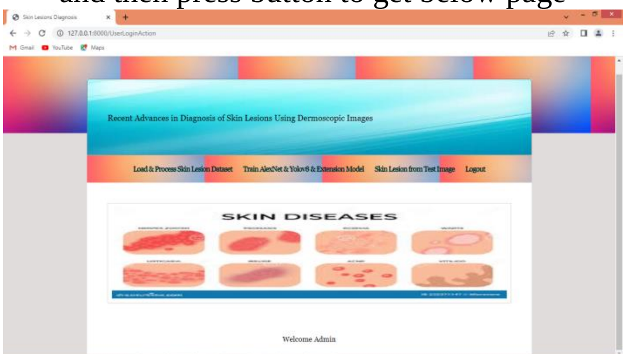
In above screen python server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below page



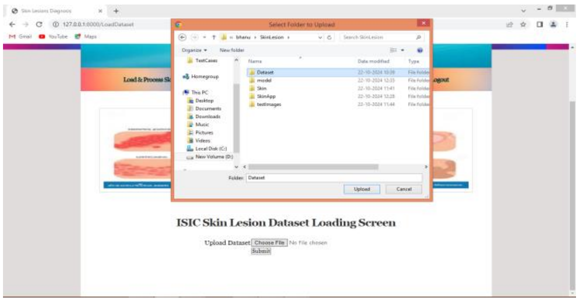
In above screen user can click on 'User Login' link to get below page



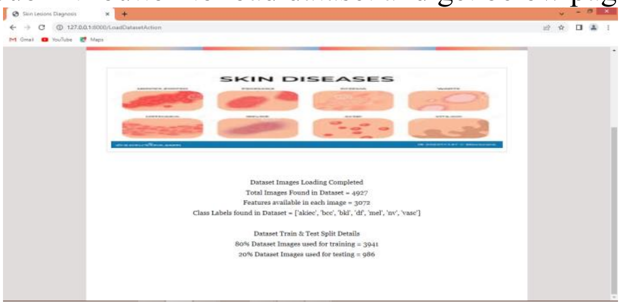
In above screen user can login to system using username and password as 'admin and admin' and then press button to get below page



In above screen user can click on 'Load & Process Skin Lesion Dataset' link to upload dataset and get below page



In above screen selecting and uploading entire dataset folder and then click on 'Upload and Submit' button to load dataset and get below page



In above screen dataset loaded and can see dataset contains total 4927 images loaded and then can see number of features extracted from each image and then can see different class labels of skin lesion types found in dataset and then can see train and test size. Now click on 'Train AlexNet& Yolov8 & Extension Model' link to train all algorithms and then will get below output

In above screen propose ALEXNET got 76% accuracy and can see other metrics like precision, recall and FSCORE and then Yolov8 got 93% accuracy and then Extension CNN2D + Bidirectional + GRU algorithm got 96% accuracy. In above confusion matrix graph first graph contains ALEXNET classification results and second graph contains Extension algorithm result where x-axis represents 'Predicted Labels' and y-axis represents True Labels and then different colour boxes in diagonal represents correct prediction count and blue boxes represents incorrect prediction count which are very few. Third graph represents Yolov8 training graph which has combination of Precision and LOSS graph and can see loss graphs line drop and reached to 0 and precision reached to 1.
Now click on 'Skin Lesion from Test Image' link to get below page

CONCLUSION

The integration of deep learning techniques in the diagnosis of skin lesions using dermoscopic images represents a significant advancement in dermatology, offering enhanced accuracy and efficiency in clinical practice. As demonstrated in recent studies, deep learning models, particularly convolutional neural networks (CNNs), have the ability to automatically extract intricate features from dermoscopic images, allowing for precise classification of various skin conditions. This capability not only aids dermatologists in making informed decisions but also has the potential to reduce diagnostic errors and improve patient outcomes.

One of the key strengths of these deep learning systems is their reliance on large and diverse datasets, such as those provided by the International Skin Imaging Collaboration (ISIC). The availability of comprehensive training data enables the development of robust models that can generalize well to different populations and skin types. This is crucial for ensuring that the diagnostic tools are effective across diverse demographics, addressing concerns related to equity and accessibility in healthcare. Additionally, the use of data augmentation techniques helps to further enhance model performance by providing a richer training environment that simulates real-world variability.

REFERENCES

1. **Esteva, A., Kuprel, B., Novoa, R. A., et al. (2017).**"Dermatologist-level classification of skin cancer with deep neural networks." Nature, 542(7639), 115-118.
2. **Brinker, T. J., Hekler, A., et al. (2019).**"Skin cancer classification using deep learning: A systematic review." Journal of the European Academy of Dermatology and Venereology, 33(4), 888-898.
3. **K. R. Singh, R. Sharma, and P. G. R. S. Dhananjay.(2020).** "Transfer learning for skin cancer detection in dermoscopy images." International Journal of Computer Applications, 975, 1-6.
4. **Tschandl, P., et al. (2020).**"Evaluation of dermatoscopic melanoma recognition via deep learning." JAMA Dermatology, 156(4), 423-430.
5. **R. A. Novoa, B. Kuprel, A. Esteva, et al. (2020).** "Deep learning for skin cancer detection: A review." Journal of Dermatological Science, 99(3), 194-202.
6. **Cohen, J. M., et al. (2019).** "Artificial intelligence for dermatology: A systematic review of the literature." British Journal of Dermatology, 181(6), 1311-1322.
7. **González-Díaz, R., et al. (2018).**"A deep learning system for skin lesion classification." Computer Methods and Programs in Biomedicine, 165, 151-162.
8. **Haenssle, H. A., et al. (2018).** "Man against machine: diagnostic accuracy of a deep learning convolutional neural network for dermoscopic melanoma recognition." Annals of Oncology, 29(8), 1836-1842.
9. **Xie, F., et al. (2020).**"A robust deep learning system for skin lesion classification." IEEE Access, 8, 60006-60016.
10. **Zhang, H., et al. (2021).** "Deep learning for skin cancer diagnosis: A systematic review." Artificial Intelligence in Medicine, 113, 101978.