ÇANKAYA UNIVERSITY
COMPUTER ENGINEERING DEPARTMENT

CENG 407

LITERATURE REVIEW

A Review of the Computer Science Literature Relating to Skinalyzer (AI-Based Skin Cancer Detection)

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Abstract

This project aims to develop a more sensitive and scalable machine learning model by combining incremental learning and federated learning techniques, focusing on skin cancer detection. Incremental learning allows the model to increase its accuracy as new data streams are integrated; thus, the model is updated as new images are added, improving its performance. Federated learning, on the other hand, enables processing in a distributed manner without transferring the data to a central server, protecting user privacy and allowing the model to be updated on various devices. The ISIC 2019 Skin Lesion Images for Classification and HAM10000 datasets used in our study provide a large sample of skin lesions that help the model recognize different types of skin cancer. These methods ensure that the model is privacy-aware and continuously updatable, while encouraging the effective use of AI-supported diagnostic systems in the healthcare field. As a result, this project aims to make an innovative contribution to personalized and sensitive diagnoses by integrating dynamic and reliable AI solutions into healthcare technologies.

Introduction

In recent years, advances in the field of artificial intelligence have caused radical changes in many areas, especially in the healthcare sector. Artificial intelligence technology enables diseases to be diagnosed quickly and with high accuracy rates by utilizing big data. Artificial intelligence algorithms, especially in the detection of abnormalities such as tumors, lesions, and aneurysms, enable images to be evaluated more quickly and precisely. In our graduation project, we plan to use incremental learning and federated learning techniques in skin cancer diagnosis; because incremental learning increases diagnostic accuracy by allowing the model to be constantly updated, while federated learning protects patient privacy by enabling transactions between devices without transferring data to a central server. Processing of image data enables detailed analysis of skin lesions, contributing to the accurate recognition of different types of skin cancer, and supports the training of the model with a wide range of data. These two methods allow the model to be trained on various datasets while preserving the confidentiality of the data, thus strengthening its capacity to recognize different types of skin cancer and providing a more scalable structure.

Incremental Learning

Incremental Learning is a machine learning technique that enables a model to learn continuously by incorporating new data over time without retraining from scratch. Unlike traditional methods where models are trained on a fixed dataset, incremental learning allows the model to update its knowledge dynamically as new information becomes available. This approach is particularly useful in scenarios where data is constantly evolving, such as medical diagnostics, where new patient data can improve the model’s accuracy and adaptability. By retaining prior knowledge while learning from new data, incremental learning ensures that the model remains current, effective, and efficient, making it highly valuable for applications that require continuous improvement. Incremental learning is effectively used with image datasets, where new visual data is continuously added. In medical imaging, for example, this approach allows the model to learn new patterns from incoming images without forgetting prior knowledge, thus improving diagnostic accuracy over time. By progressively incorporating new image data, incremental learning enhances the model's ability to handle diverse and dynamic visual information, making it ideal for applications where data is frequently updated.

There are some academic studies using incremental learning methods on ISIC2019 and HAM10000 datasets and other image datasets.

Study Title	CNN Model	Metrics	Incremental Model
Development and Validation of Adaptable Skin Cancer Classification System Using Dynamically Expandable Representation [1]	Expandable CNN with convolutional layers, batch normalization, dropout, ReLU, and softmax for classification.	Accuracy: 80.88%, Weighted-Average Precision:91.9%, Weighted-Average Recall: 80.9%, Weighted-Average F1-Score: 84.8%, AUC: 94.3% (HAM10000), External Validation AUC: 91.1% (ISIC 2019)	Dynamic Architecture, where only the last layers are modified for new classes.
AMIAC: Adaptive Medical Image Analysis and Classification Framework [2]	CNN with batch normalization	Accuracy: 97.811%, F1 Score: 97.35%, Precision:97.19%, Efficiency: High	Adaptive Learning combined with incremental learning, which uses batch normalization and dropout adjustments for new classes.
BLSNet: Skin Lesion Detection and Classification Using Broad Learning System with Incremental Learning Algorithm [3]	Broad Learning System with CNN backbone for feature extraction.	Accuracy: 99.09%, F1 Score: 98.73%, Execution Time: 0.93 seconds	Broad Learning with incremental node addition, which expands the network architecture without retraining.
An Appraisal of Incremental Learning Methods [4]	Progressive Neural Networks (PNN)	EWC Accuracy: 94.5 % on permuted MNIST, SI Accuracy: 97.5% on MNIST, ICaRL Accuracy: around 62.5 – 67 % on CIFAR-100	Elastic Weight Consolidation (EWC), iCaRL (Incremental Classifier and Representation Learning), SI (Synaptic Intelligence), PNN
Comparing Incremental Learning Strategies for Convolutional Neural Networks [5]	Convolutional Neural Networks (CNN)	CaffeNet + Svm Accuracy: from 41.63% to 66.97% (iClubWorld28), CaffeNet + Ft Accuracy: 78.4%, Vgg_Face+SVM Accuracy: 96.73%	LeNet7: A seven-layer CNN, CaffeNet + SVM, CaffeNet + Fine Tuning (FT), VGG_Face + SVM

The first academic study on the table: **Development and Validation of Adaptable Skin Cancer Classification System Using Dynamically Expandable Representation** aimed to develop a scalable skin cancer classification model using the Dynamically Expandable

Representation (DER) algorithm with incremental learning to enhance diagnostic accuracy and adaptability. Trained on the HAM10000 and ISIC 2019 datasets, the model progressively expands its classification capacity to recognize a wide range of skin lesions. Based on the ResNet-50 architecture, the model uses data augmentation techniques, including horizontal flipping, contrast-brightness adjustments, and distortion, to increase robustness against variations. Achieving a weighted-average precision of 0.918, recall of 0.808, F1-score of 0.847, and an AUC of 0.943 on the HAM10000 dataset, the DER model outperformed traditional methods in accuracy and adaptability, with an AUC of 0.911 on the ISIC 2019 validation. This incremental learning approach successfully mitigates catastrophic forgetting, enabling the model to retain knowledge from prior classes while effectively integrating new data.

Second study: **AMIAC** presents an adaptive self-learning framework for medical image analysis, allowing deep learning models to adapt to changing image distributions over time. The framework combines manual and CNN-based feature extraction, enhancing model accuracy and reducing the need for retraining. Manual features capture specific image details, while pre-trained CNNs extract abstract features, providing complementary information. Trained initially on a large dataset, the model adapts to new imaging modalities through transfer and incremental learning. The framework achieved high performance, with an F1-score of 97.35 ± 0.39, precision of 97.19 ± 0.51, and accuracy of 97.81 ± 0.35, indicating its potential as a tool for supporting pathologists in diagnosis.

BLSNet: Skin Lesion Detection and Classification Using Broad Learning System with Incremental Learning Algorithm: The BLSNet model in this paper is based on a Broad Learning System (BLS) architecture, which emphasizes wide feature representations rather than deep stacking of layers. This approach is combined with incremental learning techniques, allowing the model to learn new data classes without retraining on the entire dataset, a critical feature in handling continuously updated medical image datasets. For feature extraction, BLSNet uses a combination of manual and CNN-based features, where the manual features capture specific skin lesion characteristics, while the CNN-based features are extracted from pretrained models. To further enhance the robustness of the model, data augmentation techniques are applied, including horizontal flips, random contrast and brightness adjustments, and distortion to simulate variations in real-world image conditions. This allows the model to generalize better across different imaging conditions. During training, an auxiliary loss function is applied to balance knowledge from previously learned and new classes, thus mitigating catastrophic forgetting. The BLSNet achieves high performance on ISIC 2019 and PH2 datasets, with an accuracy of 99.09% and an F1-score of 98.73%, as well as a low processing time of 0.93 seconds per image, making it both precise and efficient.

Federated Learning

Federated learning is a method that enables machine learning models to be trained on distributed data located on different devices or systems without the need to centralize the data on a server. In this model, each device or system trains the model on its local data and only sends the model parameters to the central server. This approach prevents data from leaving the device, thus preserving data privacy, while also significantly reducing network traffic. The central server combines the parameters from devices to update the model and then sends the updated model back to the devices. This iterative process allows the model to continuously improve without data ever leaving the devices. Federated learning offers a major advantage in areas with sensitive data, such as healthcare, by enhancing security in medical applications and protecting patient privacy; for example, electronic health records, including lab results, biomedical images, and vaccination status, can be processed as primary health data sources for machine learning applications without leaving the device.[6] In this way, data privacy is preserved, and powerful, secure, and continuously learning models are developed by staying up to date with local data on devices.

Study Title	CNN Model	Metrics	Federated Model
Federated Machine Learning for Skin Lesion Diagnosis: An Asynchronous and Weighted Approach [7]	CNN and CNN components Convolutional layers, Max-pooling layers, Fully connected layers, Dropout regularization	F1: 94.8, Sensitivity: 94.1, Recall: 92.6, Specify: 96.3, Loss: 1.6, Precision 96.7, Accuracy: %92	Asynchronous federated learning (Async-FL)
Federated and Transfer Learning Methods for the Classification of Melanoma and Nonmelanoma Skin Cancers: A Prospective Study [8]	CNN and CNN architectures, including ResNet, VGG, DenseNet, GoogLeNet, and MobileNet.	AUC: 99.43% Accuracy: 94.17% Recall rate: 93.76% Precision: 94.28% F1-score: 93.93%	Transfer learning , fine-tuning and semi-supervised FL framework motivated by a peer learning (PL)
Deep Learning Espoused Imaging Modalities for Skin Cancer Diagnosis: A Review [9]	Generative Adversarial Network (G-AN)	Accuracy: %98.5 , Sensevity: % 95, Specify: %92, Dice Coefficient: %96	Federated Learning (FL)
An Adaptive Federated Machine Learning-Based Intelligent System for Skin Disease Detection: A Step toward an Intelligent Dermoscopy Device [10]	Convolutional Neural Networks (CNNs) Single-instance optimized CNN model Dynamic ensemble classifiers	Accuracy: %95.6, Recall:%95, Precision :%95	Online training (OT), Federated Learning, Online classifier updating (OCU)

Federated Machine Learning for Skin Lesion Diagnosis: An Asynchronous and Weighted Approach

The first article on the table focuses on enhancing skin cancer detection while preserving privacy through various techniques: asynchronous federated learning (Async-FL) for efficient model updates, convolutional neural networks (CNNs) for feature extraction, layer-by-layer asynchronous updates to minimize communication load, dropout regularization to reduce overfitting, and a client selection algorithm to optimize accuracy based on data and hardware. This combination aims to improve diagnostic performance effectively. The study's results using asynchronous federated learning (Async-FL) and convolutional neural networks (CNNs), with an F1 score of 94.8, sensitivity of 94.1, recall of 92.6, specificity of 96.3, precision of 96.7, and accuracy of 92%. The model's loss was recorded at 1.6, indicating strong performance in skin cancer detection while maintaining privacy and efficiency.

Federated and Transfer Learning Methods for the Classification of Melanoma and Nonmelanoma Skin Cancers: A Prospective Study

The study investigates various federated learning (FL) and transfer learning (TL) techniques for classifying melanoma and nonmelanoma skin cancer. It emphasizes ensemble methods that integrate multiple CNN architectures, such as ResNet, VGG, and DenseNet, which significantly improve classification accuracy. Notably, one study achieved a remarkable area under the curve (AUC) of 99.43%, with an accuracy of 94.17%, recall of 93.76%, precision of 94.28%, and an F1-score of 93.93%. This review synthesizes findings from a systematic search across benchmark datasets, including HAM10000, to highlight recent FL and TL algorithms for early-stage treatment.

Deep Learning Espoused Imaging Modalities for Skin Cancer Diagnosis: A Review

The objective of this article is to deliver a thorough examination of the progress, obstacles, and prospective applications within this vital area of dermatology. In this study, various neural network architectures were evaluated for skin cancer detection, including Generative Adversarial Network (G-AN), Artificial Neural Network (A-NN), Convolutional Neural Network (C-NN), and Kernel-based SNN (KSNN). Among these, the G-AN achieved the best performance, yielding an Area Under the Curve (AUC) of 98.5%, a sensitivity of 95%, a specificity of 92%, and a Dice Coefficient (DC) of 96%. This highlights the G-AN's superior capability in accurately detecting skin cancer lesions.

An Adaptive Federated Machine Learning-Based Intelligent System for Skin Disease Detection: A Step toward an Intelligent Dermoscopy Device

The article proposes an adaptive federated learning model designed for skin disease diagnosis, centering on an ensemble CNN as the main classifier to support intelligent dermoscopy applications. A single instance optimized CNN model is incorporated within the cloud server's ensemble to enhance adaptability. Key contributions include model deployment across both cloud servers and edge devices, facilitating continuous updates through online training (OT) and online classifier updating (OCU). Using TensorFlow Federated and Federated Core APIs, this approach provides robust performance while adapting to new disease data. Results indicate an accuracy of 95.6%, recall of 95%, and precision of 95%, demonstrating the model's effective and reliable diagnostic capability.

PAPER NAME	IMAGE PROCESSING	METRICS	INCREMENTAL LEARNING	FEDERATED LEARNING
Incremental Learning and Federated Learning for Heterogeneous Medical Image Analysis	Traditional Deep Learning and CNN	*CCSI accuracy: **79.10%** (BloodMnist Dataset) *FedImpres (Medical init): **94.2%** (a=0.01 epoch=5 BloodMNIST Dataset) *FedImpres w constrained CE loss: **80.6%** (α = 0.005, epoch= 10, Retina Dataset)	Continual Normalization model structure to restore Continual Class-Specific Impression	FedCurv for Catastrophic Forgetting, Transfer Learning, FedImpress

The thesis[11] aims to improve the adaptability of deep learning (DL) models in real-world settings, where data is often heterogeneous, making it crucial to enhance these models' practical utility. A combined approach using incremental and federated learning, as discussed in the paper *"Incremental Learning and Federated Learning for Heterogeneous Medical Image Analysis,"* strategically addresses two major challenges in medical imaging: the need for continuous learning with new data and the requirement for data privacy across multiple institutions. This dual approach not only enables DL models to evolve with new disease classes but also ensures that data remains localized, preserving patient confidentiality.

By combining incremental and federated learning, this methodology offers a robust solution to meet evolving healthcare demands. Incremental learning combats "catastrophic forgetting," allowing the model to retain knowledge of prior disease classes while adapting to new ones. Federated learning, on the other hand, facilitates collaborative model training across institutions without centralizing sensitive data, thereby enhancing privacy. Together, these methods allow the model to generalize effectively across diverse datasets from various institutions, addressing "domain shift" challenges stemming from differing imaging protocols. This approach also minimizes the need for extensive data transfers and retraining, making it resource-efficient and adaptable to institutions with varied computational resources.

However, implementing both frameworks together is not without challenges. It demands precise model updates and coordination across clients, adding complexity to the system. Additionally, while synthetic data is valuable for privacy preservation, it may not fully capture real-world distributions, potentially reducing model accuracy over time if not carefully calibrated. These limitations underscore the need for rigorous model tuning and effective communication between institutions to optimize the potential of this advanced approach.

Contribution

This project aims to advance the application of artificial intelligence in skin cancer detection by combining incremental and federated learning techniques on the ISIC2019 and HAM10000 datasets. This hybrid approach addresses two critical needs in medical AI: adaptability and privacy. Incremental learning allows our model to dynamically integrate new data over time, continuously enhancing diagnostic accuracy without the need for retraining and without compromising performance metrics such as accuracy. Federated learning, on the other hand, ensures that sensitive patient data remains decentralized by training across distributed devices without transferring information to a central server, thereby promoting data privacy.

Using both the ISIC2019 and HAM10000 datasets, our model will gain exposure to a wide range of skin lesion images, enhancing its ability to generalize across different types of skin cancer. This approach not only improves the model's scalability and privacy but also contributes to a more personalized, up-to-date, and secure diagnostic solution in dermatology. Through this innovative combination, we aim to set a new standard in real-world healthcare AI applications, where continuous learning, privacy preservation, and stable accuracy are critical.

In the incremental learning phase, we will use the **novel data-free class-incremental learning approach** combined with **Continual Class-Specific Impression (CCSI)**, implemented in **PyTorch**. This combination enables the addition of new classes without accessing old data, effectively minimizing knowledge loss while preserving class-specific impressions in the model's memory. To further enhance the approach, we will integrate **Flower** for federated learning. The data privacy and distributed learning capabilities of federated learning, combined with our incremental learning strategies, allow each device to learn using only its own data while retaining previous class impressions, thereby strengthening the model's long-term memory and overall performance.

References

[1] Jang, Bong Kyung, and Yu Rang Park. "Development and Validation of Adaptable Skin Cancer Classification System Using Dynamically Expandable Representation." *Healthcare Informatics Research* 30.2 (2024): 140-146.

[2] Iqbal, Saeed, et al. "AMIAC: adaptive medical image analyzes and classification, a robust self-learning framework." *Neural Computing and Applications* (2023): 1-29.

[3] Gottumukkala, VSSP Raju, N. Kumaran, and V. Chandra Sekhar. "BLSNet: Skin lesion detection and classification using broad learning system with incremental learning algorithm." *Expert Systems* 39.9 (2022): e12938.

[4] Luo, Yong, et al. "An appraisal of incremental learning methods." *Entropy* 22.11 (2020): 1190.

[5] Lomonaco, Vincenzo, and Davide Maltoni. "Comparing incremental learning strategies for convolutional neural networks." *Artificial Neural Networks in Pattern Recognition: 7th IAPR TC3 Workshop, ANNPR 2016, Ulm, Germany, September 28–30, 2016, Proceedings 7*. Springer International Publishing, 2016.

[6] NERGİZ, M. "Collaborative Artificial Intelligence Concept: Federated Learning Review." *DÜMF Mühendislik Derg* (2022).

[7] Yaqoob, Muhammad Mateen, et al. "Federated machine learning for skin lesion diagnosis: an asynchronous and weighted approach." *Diagnostics* 13.11 (2023): 1964.

[8] Riaz, Shafia, et al. "Federated and Transfer Learning Methods for the Classification of Melanoma and Nonmelanoma Skin Cancers: A Prospective Study." *Sensors* 23.20 (2023): 8457.

[9] Sumaiya, Noor, and Anooja Ali. "Federated Learning Assisted Deep learning methods fostered Skin Cancer Detection: A Survey." *Frontiers in Biomedical Technologies* (2024).

[10] Hashmani, Manzoor Ahmed, et al. "An adaptive federated machine learning-based intelligent system for skin disease detection: A step toward an intelligent dermoscopy device." *Applied Sciences* 11.5 (2021): 2145.

[11] Ayromlou, Sana. *Incremental learning and federated learning for heterogeneous medical image analysis*. Diss. University of British Columbia, 2023.

https://www.innova.com.tr/blog/Yapay-zeka-ile-saglik-sektorunde-hastalik-teshisinde-devrim