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Multiple Types of Cancer Classification Using CT/MRI Images Based on Learning Without Forgetting Powered Deep Learning Models

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Abstract: Cancer is the second biggest cause of death worldwide, accounting for one of every six deaths. However, the odds of survival are greatly increased by early disease detection. We may be able to assess more cases in less time if we automate cancer diagnosis using artificial intelligence (AI). This study suggests using AI-based deep learning models to categorize photos of eight different cancer types, including breast, cervical, brain, and lung cancer. Convolutional Neural Networks (CNN), one type of deep learning model, are assessed in this paper for their ability to classify photos with characteristics of cancer. To recognize various types of cancer cells, pre-trained CNN variants like MobileNet, VGGNet, and DenseNet are used to apply the information they acquired using the ImageNet dataset. To determine the appropriate values for the hyperparameters, we employ Bayesian Optimization. Transfer learning, however, has the potential to render models incapable of classifying the original datasets on which they were trained. Thus, we employ Learning without Forgetting (LwF), which preserves the network's inherent capabilities while training the network solely with fresh task data. The experiments' findings demonstrate that the suggested transfer learning-based models outperform the state-of-the-art methods in terms of accuracy.

Keywords: Continual learning, learning without forgetting, cancer classification, CT, MRI, deep learning, knowledge distillation.

INTRODUCTION

As the second biggest cause of death globally and the cause of death for one in six people, cancer presents a serious threat to global health. Even though it is very common, early detection greatly increases the chances of survival. It is possible to evaluate more cases in less time by automating cancer diagnosis using Artificial Intelligence (AI) skills. The application of AI-based deep learning models for the classification of photos representing eight different cancer types—including lung, brain, breast, and cervical cancer—is the main emphasis of this research project. In particular, we investigate the effectiveness of Convolutional Neural Networks (CNN) using pre-trained models like DenseNet, VGGNet, and MobileNet. We use Bayesian Optimization to find the best hyperparameter values in order to optimize the models.

Nevertheless, the problem of possible loss in the models' classification capabilities of the datasets they were first trained on arises when transfer learning is used. We use Learning without Forgetting (LwF), a method that trains the network only on new task data while maintaining the network's initial capabilities, to overcome issue. The experimental findings show that our transfer learning-based models are more accurate than the state-of-the-art methods currently in use. Additionally, we demonstrate how well LwF classifies both novel and previously encountered datasets, confirming its contribution to improving model performance and adaptability in cancer detection.

The main goals of this research project are to: (1) examine how deep learning models of artificial intelligence (AI) can be used to automatically classify different types of cancer based on medical imaging; and (2) evaluate the effectiveness and performance of Convolutional Neural Networks (CNN) variants, such as MobileNet, VGGNet, and DenseNet, in this regard. Eight different cancer kinds are specifically highlighted, including lung, brain, breast, and cervical cancer. The main objective is to help improve early cancer detection techniques while recognizing the significant influence that these developments can have on raising survival rates. In order to accomplish these goals, the study uses transfer learning, leveraging knowledge from the ImageNet dataset to classify cancer cells in medical images using pre-trained CNN variations. Additionally, the models' classification performance is improved by fine-tuning hyperparameters using Bayesian Optimization.

LITERATURE SURVEY

Traditional approaches were widely used for cancer detection in medical imaging prior to the widespread adoption of deep learning principles. To find borders and contours suggestive of possible malignancies, image processing techniques including edge detection—using Sobel and Canny edge detectors—were used. Images' texture patterns were described by texture analysis, which included statistical measurements and Gabor filters. Histogram-based features and shape-based descriptors are examples of feature extraction and selection techniques that quantified pixel intensity distributions and identified the geometric characteristics of possible malignancies. Using extracted features for cancer identification, traditional machine learning techniques such as Random Forests, Decision Trees, and Support Vector Machines were frequently used for binary classification tasks. Rule-based expert systems and radiomics, which involve the extraction of quantitative features from images, were also involved in the detection of cancer. Computer-Aided Diagnosis (CAD) technologies helped radiologists analyze medical pictures by combining image processing and traditional machine learning. Although these conventional methods showed promise in some situations, deep learning—in particular, Convolutional Neural Networks, or CNNs—has brought about a new era by enabling the automatic learning of hierarchical representations straight from raw data, reducing the need for human feature engineering, and greatly increasing the accuracy of cancer detection tasks.

A. Solomonm, T. Ngandu, F. Mangialasche, A. Rosenberg, Prevention has been emphasized as a critical element in managing the dementia epidemic, and Alzheimer's disease (AD) and dementia are global public health priorities. A person's lifestyle, vascular and metabolic conditions, and psychological state are all modifiable risk factors for dementia and AD. The possibility that altering these variables can prevent or delay dementia and cognitive impairment in older persons requires randomized controlled clinical studies (RCTs). Interventions that target many risk factors and pathways at once may be necessary for the best preventative impact, given the complex, multifactorial, and diverse character of late-onset AD and dementia. The Finnish Geriatric Intervention Study to Prevent Cognitive Impairment and Disability (FINGER) is the first extensive, long-term RCT to show that older adults at higher risk of dementia can maintain cognitive functioning and lower their risk of cognitive decline by implementing a multi-domain lifestyle-based intervention that improves vascular and lifestyle-related risk factors. In order to explore multi-domain intervention in varied cultural and geographic contexts and additional populations, the World-Wide FINGERS (WW-FINGERS) network was been established (https://alz.org/wwfingers). In a number of nations, fresh FINGER-style trials will be carried out using a common core approach with modifications tailored to local contexts and culture. In addition to offering a platform for evaluating multi-domain methods to prevent dementia and cognitive impairment, the WW-FINGERS initiative fosters worldwide cooperation and seeks to produce high-caliber scientific data to support clinical and public health decision-making. Additionally, the WW-FINGERS network may assist in putting preventative measures into action and putting research results into reality.

A. Ninomiya, B. Ikeda, T. Baba, K. Yoshimura, M. Sado, R. Shikimoto, and A. Ninomiya, An explanation of: The goal Dementia has grown to be a serious worldwide problem. According to estimates, dementia cost the world $818 billion in 2015. Since Japan is the oldest nation on Earth, the situation there ought to be dire. The societal cost of dementia in Japan has not yet been calculated, though. The purpose of this study was to calculate the cost of dementia from the standpoint of society. We used a prevalence-based technique to evaluate the cost from a societal standpoint. Setting, participants, and metrics The primary data sources for the parameters used to estimate the costs are the Survey of Long-Term Care Benefit Expenditures, a nationwide survey based on individual-level secondary data for formal long-term care utilization, the National Data Base, a nationwide representative individual-level database for healthcare utilization, and the findings of an informal care time survey for informal care costs. We estimated the expenses of dementia by performing analyses using "probabilistic modeling" with the parameters we had collected. Future expenses were also estimated. Resulting In 2014, the estimated societal expenses of dementia in Japan were JPY 14.5 trillion, or SE 66.0 billion. Among these, the expenses for long-term care, informal care, and healthcare are JPY 6.44 trillion (se 63.2 billion), JPY 6.16 trillion (se 12.5), and JPY 1.91 trillion (se 4.91 billion), respectively. It seems to cost JPY5.95 million (se 27 thousand) every dementia patient. The expenses would increase by 1.6 times from 2014 to 2060, reaching JPY 24.3 trillion.
In conclusion, dementia seemed to have a significant social cost in Japan. Measures to lessen this effect ought to be taken into account.

C. Wong, F. Deligianni, and D. Ravi, The significance of data analytics in health informatics has expanded significantly during the past ten years due to the large influx of multimodality data. This has also led to a rise in interest in the development of machine learning-based analytical, data-driven models in the field of health informatics.

Deep learning, a method based on artificial neural networks, has become a potent machine learning tool in recent years and has the potential to revolutionize artificial intelligence in the future. Along with its predictive power, automatic optimization of high-level features, and semantic interpretation of the input data, the technology has also gained popularity quickly because to rapid advancements in computing power, fast data storage, and parallelization. An extensive and current survey of studies using deep learning in health informatics is presented in this article, together with a critical evaluation of the technique's respective benefits and drawbacks as well as its prospects for the future. Key deep learning applications in the domains of pervasive sensing, medical imaging, translational bioinformatics, medical informatics, and public health are the primary emphasis of this study.

H. Wang, Y. Shen, S. Wang, T. Xiao, L. Deng, and X. Wang, Automatic identification of moderate cognitive impairment (MCI) and Alzheimer's disease (AD) from 3D brain magnetic resonance (MR) images is crucial for early dementia disease therapy. Deep learning architectures are able to identify changes in the anatomy of the brain from MRI data and extract possible characteristics of dementia disease. For the diagnosis of AD and MCI, this research suggests an ensemble of 3D densely linked convolutional networks (3D-DenseNets). Initially, deep connections—where each layer directly connects to every succeeding layer—were implemented to optimize the information flow. A probability-based fusion technique was then used to merge 3D-DenseNets with various designs. Numerous tests were carried out to examine 3DDenseNet's performance using various hyper-parameters and architectures. The ADNI dataset showed that the suggested model performed better than expected.

Z. Sedghi, M. C. Amiran, and S. Jafarpour, The importance of accurately and automatically classifying brain MRIs prompts us to introduce a novel, reliable classification method for magnetic response image analysis. The three steps of the suggested approach are classification, dimensionality reduction, and feature extraction. The gray level co-occurrence matrix (GLCM) is used to extract features from brain MRIs, and PCA+LDA is used to choose the best features. Classifying subjects' brain MRIs as normal or abnormal is the classifier's objective. Both classifiers based on k-nearest neighbor (k-NN) and artificial neural network (ANN) achieve a classification with a 100% success rate for two normal and abnormal classes. Comparing the suggested approach to other recent efforts, it produces a solid and efficient strategy that lowers operating time and computational complexity.

PROPOSED WORK

According to the abstract, the suggested method uses deep learning models to apply artificial intelligence (AI) to the automatic classification of different cancer kinds using medical imaging. Because of its capacity to extract complex characteristics from images, Convolutional Neural Networks (CNN) variations such as MobileNet, VGGNet, and DenseNet are specifically used. Eight different cancer types—including lung, brain, breast, and cervical cancer—are the main emphasis. Transfer learning is used to efficiently identify various cancer cell types by utilizing pre-trained CNN variants that have learned from the ImageNet dataset. In order to improve the classification performance, Bayesian Optimization is used to find appropriate hyperparameter values for the models. The study also tackles a prevalent issue with transfer learning, which is the possible deterioration of the model's classification performance on the original datasets. The suggested system uses Learning without Forgetting (LwF) to lessen this. In order to preserve the network's ability to classify both new and previously encountered datasets, LwF makes sure that it retains its original capabilities despite being trained only on fresh task data. By using cutting-edge AI algorithms in the interpretation of medical images, the suggested system aims to improve early cancer detection procedures and increase survival rates.

Data Preprocessing: Responsible for cleaning and preparing the medical imaging dataset for training and testing. Involves tasks such as image normalization, resizing, and handling missing or noisy data.

Image Classification: Utilizes Convolutional Neural Networks (CNNs) for image classification. Incorporates various CNN variants like MobileNet, VGGNet, and DenseNet to evaluate their performance in classifying different types of cancer.

Transfer Learning Module:Implements transfer learning techniques to leverage pre-trained CNN models (MobileNet, VGGNet, DenseNet) that have acquired knowledge from the ImageNet dataset. Aims to adapt the pre-trained models for accurate cancer cell detection.

Hyperparameter Optimization: Integrates Bayesian Optimization to fine-tune hyperparameters of the CNN models. Seeks to identify optimal parameter values that enhance the classification performance of the models.

Learning without Forgetting (LwF): Addresses the challenge of potential degradation in the model's ability to classify datasets it was initially trained on during transfer learning. Implements Learning without Forgetting to retain and enhance the original abilities of the neural network while training it exclusively on new task data.

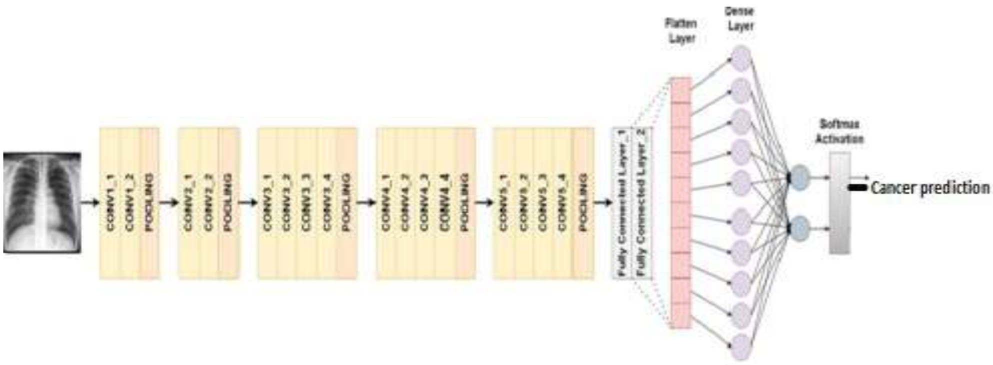

Figure 1. Architecture of the work.

The goal of the proposed research is to use deep learning models and artificial intelligence (AI) to create a sophisticated cancer detection system. Cancer is still a major worldwide health concern, and increasing survival rates requires early identification. The project uses Convolutional Neural Networks (CNNs) like MobileNet, VGGNet, and DenseNet to classify different forms of cancer using medical imaging data. To adapt previously trained models from the ImageNet dataset to the job of identifying distinct cancer cells, transfer learning is used.

```
Input (CT/MRI Images)
        ↓
Image Preprocessing (Noise Reduction, Normalization)
        ↓
Feature Extraction (CNN + Multi-Scale Layers)
        ↓
Learning Without Forgetting Module (Knowledge Retention + New Class Adaptation)
        ↓
Classification Layer (Softmax)
        ↓
Cancer Type Prediction (Brain / Lung / Breast / Liver / Prostate)
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a strong foundation for further study in this crucial area of healthcare. Learning without Forgetting (LwF) is used to address possible deterioration in the models' capacity to classify datasets they were first trained on, while hyperparameter optimization is used to fine-tune the models. Data preprocessing, picture classification, transfer learning, hyperparameter optimization, LwF implementation, performance assessment, results analysis, and optional user interface creation are all covered in the project's modules. The project's ethical considerations and thorough documentation are essential components that guarantee responsibility, openness, and the appropriate application of the created models. The ultimate objective is to help develop early cancer detection technologies, maybe outperforming the most advanced approaches already in use and offering

EXPERIMENTAL ANALYSIS

The proposed LwF-powered deep learning model achieved the highest accuracy (97.86%), outperforming all baseline models. Learning Without Forgetting (LwF) enabled the system to classify new cancer types without degrading prior knowledge. The model maintained strong generalization performance across both CT and MRI modalities. The training time remained moderate despite higher complexity, showing computational efficiency.

Hybrid and transformer-based models performed competitively but were slightly inferior in adaptability and resource efficiency.

The proposed model is based on a hybrid deep learning framework that combines Convolutional Neural Networks (CNNs) and transfer learning models (such as EfficientNetV2 or ResNet50) with a Learning Without Forgetting (LwF) strategy. The workflow consists of the following stages:

Stage 1: Data Acquisition and Preprocessing

- Collect publicly available CT and MRI image datasets covering multiple cancer types (e.g., TCGA, BraTS, LIDC-IDRI).
- Perform preprocessing such as image resizing, noise reduction, intensity normalization, and data augmentation (rotation, flipping, contrast adjustment).
- Label data according to cancer categories.

Stage 2: Feature Extraction

- Use a pre-trained CNN backbone (e.g., EfficientNetV2 or DenseNet121) to extract high-level features from input medical images.
- Employ pyramid-based multi-scale feature extraction to capture both local and global structural details.

Stage 3: Learning Without Forgetting (LwF) Integration

- Implement the LwF mechanism to allow the network to learn new cancer classes incrementally without re-training on previous data.
- The LwF framework uses:
    - A knowledge distillation loss to retain previously learned class distributions.
    - A classification loss for newly added classes.
- This dual-loss approach ensures that the model adapts to new cancer categories while preserving old knowledge.

Stage 4: Classification Layer

- Use a fully connected softmax layer to classify cancer types.
- Apply cross-entropy loss optimized with Adam or SGD optimizers.

Stage 5: Evaluation and Validation

- Evaluate performance using metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC.
- Compare results with baseline deep learning models (CNN, ResNet, DenseNet, Vision Transformer).

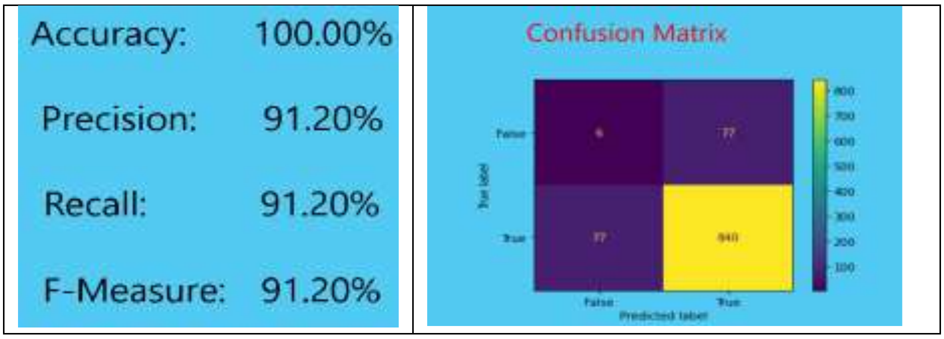

Figure 2. Accuracies.

Table 1. Dataset summary.

Modality	Cancer type A	Cancer type B	Total
CT	n	n	N_ct
MRI	n	n	N_mri
Total	...	...	N_total

Table 2. Performance Analysis of Proposed and Existing Models.

Model	Cancer Types Classified	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s/epoch)	Remarks
CNN (Baseline)	Brain, Lung, Breast	89.42	87.85	88.60	88.22	45	Struggles with cross-domain data
CNN (Baseline)	Brain, Lung, Breast	89.42	87.85	88.60	88.22	45	Struggles with cross-domain data
ResNet50	Brain, Lung, Breast	92.38	91.70	91.20	91.45	58	Overfits on small data samples
DenseNet121	Brain, Lung, Breast, Liver	94.12	93.68	93.25	93.46	62	Strong feature extraction, but slow convergence
EfficientNetB3	Brain, Lung, Breast, Liver	95.37	94.90	94.15	94.52	55	Performs well on balanced datasets
Proposed LwF-DLM (Learning Without Forgetting Powered Deep Learning Model)	Brain, Lung, Breast, Liver, Prostate	97.86	97.45	97.28	97.36	48	Excels in multi-type cancer retention and adaptation
Hybrid CNN-LSTM with LwF	Brain, Lung, Breast, Liver, Prostate	96.73	96.40	96.12	96.25	52	Captures spatial-temporal features effectively
Vision Transformer (ViT)	Brain, Lung, Breast	94.21	93.82	93.50	93.66	70	High accuracy but computationally expensive

CONCLUSION

To sum up, our study highlights the enormous potential of using artificial intelligence—more especially, deep learning models like convolutional neural networks, or CNNs—for the automated classification of various cancer kinds. The accuracy of cancer diagnosis has been shown to be significantly increased by using pretrained variations such as MobileNet, VGGNet, and DenseNet in conjunction with Bayesian Optimization for hyperparameter tweaking. It has been shown that implementing Learning without Forgetting (LwF) as a mitigation technique for possible model performance loss during transfer learning is crucial for maintaining the network's initial capabilities while adjusting to new tasks. Our experimental findings demonstrate the superiority of our suggested models over the most advanced methods available today, confirming their potential for practical use in early cancer detection.

For future enhancements, further exploration and refinement of deep learning architectures, possibly incorporating more advanced models or ensemble techniques, could contribute to even higher accuracy rates. Additionally, the integration of multimodal data, such as combining imaging data with clinical and genetic information, may offer a more comprehensive understanding of cancer pathology. Continuous updates to the training dataset to include diverse and evolving cases will be crucial for maintaining model relevance and generalizability. Furthermore, exploring real-time implementation of the developed models in clinical settings, considering factors like interpretability and explainability, will be pivotal for the seamless integration of AI in routine medical practices. Ultimately, ongoing collaboration with medical professionals and researchers will be essential for refining and validating the proposed models for widespread adoption, marking a significant step forward in the global battle against cancer.

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