Research Article

Zainab Muhammed and Belal Al-Khateeb*

CNN-EWC: A continuous deep learning approach for lung cancer classification

https://doi.org/10.1515/jisys-2024-0541
received December 25, 2024; accepted March 28, 2025

Abstract

Problem – In continuous deep learning scenarios, where the model is required to learn new tasks without losing knowledge from prior tasks, catastrophic forgetting is a significant limitation of continuous deep learning models. This problem has the highest significance in the field of medical image analysis, as it is imperative to ensure the reliability of diagnostics and prediction through consistent and accurate classification. This study solves the challenge of catastrophic amnesia in deep learning by utilizing the conjunction of Convolutional Neural Networks (CNNs) with the Elastic Weight Consolidation (EWC) called CNN-EWC model.
Aims – This research seeks to develop a continuous learning pipeline for classifying histopathology images of lung cancer into lung benign tissue (*n*), lung adenocarcinoma (ACA), and lung squamous cell carcinoma (SCC). A dataset of 15,000 images equally across these three classes is used to comprehensively evaluate the proposed method in a realistic medical diagnostic scenario.
Methods – The suggested CNN-EWC method mitigates catastrophic forgetting in continuous deep learning by safeguarding critical parameters across tasks. The model is trained successively on three tasks, utilizing EWC to inhibit substantial alterations to essential parameters. This ensures a preservation of knowledge from previous tasks while accommodating new tasks. The methodology preserves elevated classification precision in medical diagnostics by balancing stability and adaptability.
Results – The CNN-EWC model experimental results achieved testing accuracy from 98 to 99.6%. Notwithstanding a diversity in dataset size (3,000, 4,500, and 6,000 images), the model performed excellently for lung n, lung ACA, and SCC, its good statistics hold true for all three diseases tested on the testing dataset. External tests were conducted on (3–1,500) images to verify the accuracy of the model's classification and prediction, and the accuracy reached 100%, which indicates that the problem of catastrophic forgetting that occurs in continuing education has been addressed.
Conclusions – The CNN-EWC model has proven its effectiveness in continuous training in terms of accuracy, speed, saving time, and correct classification of images as it solves catastrophic forgetting but also maintains very high classification performance. In medical imaging, the simple switching logic effectively solves several simulations of catastrophic forgetting by avoiding back propagation for large numbers of images or by direct calculation.

Keywords: CNN-EWC, lung cancer classification, lung cancer detection, continuous deep learning, catastrophic forgetting

*** Corresponding author: Belal Al-Khateeb,** College of Computer Science and Information Technology, University of Anbar, 10003, Ramadi, Iraq, e-mail: belal-alkhateeb@uoanbar.edu.iq
Zainab Muhammed: Informatics Institute for Postgraduate Studies, Information Technology & Communication University, Baghdad, 10069, Iraq; Computer Science Department, College of Education for Pure Science/Ibn-Al Haitham, University of Baghdad, Baghdad, 10071, Iraq, e-mail: phd202220704@iips.edu.iq, zainab.m@ihcoedu.uobaghdad.edu.iq

1 Introduction

The field of medical imaging has experienced a transformative revolution with the introduction of deep learning techniques, particularly in the detection and diagnosis of lung cancer. Convolutional Neural Network (CNN) and advanced deep learning architecture have exhibited unparalleled capabilities in analysis of medical images, often surpassing or matching the performance of human experts [1–3].

In recent studies, the potential of deep learning to detect early-stage lung cancer has been demonstrated. Machine learning models have exhibited exceptional sensitivity in the identification of subtle radiological patterns that may evade traditional diagnostic methods. For pulmonary image analysis, researchers developed sophisticated neural network architectures. In a multitude of clinical datasets, these architectures have obtained detection accuracy that surpassed 95% [4,5].

In the detection of lung cancer, the primary benefits of deep learning are as follows: Enhanced feature extraction capabilities, the capacity to process complex multi-dimensional imaging data, the potential for early and more accurate diagnostic predictions, and reduced inter-observer variability in image interpretation [6,7].

Despite these developments, there are still substantial obstacles to overcome, such as the necessity for extensive annotated datasets, the generalizability of the model, and the capacity to adjust to the changing landscape of medical imaging technologies [8].

The fundamental challenge of knowledge retention and adaptation in neural networks is addressed by continuous or perpetual learning, which represents a critical frontier in machine learning.

Elastic Weight Consolidation (EWC) is a critical approach for preventing catastrophic forgetting, a phenomenon in which neural networks swiftly overwrite previously learned information when they are trained on new tasks [9–13].

EWC introduces a sophisticated regularization technique that effectively enables models to learn new information while maintaining previously acquired knowledge, preserving key network parameters during subsequent training iterations of the model. EWC facilitates more adaptive and stable learning processes by estimating parameter importance using a probabilistic framework [14–18].

Current deep learning models for lung cancer diagnosis encounter significant obstacles, such as catastrophic forgetting, reliance on extensive annotated datasets, inadequate generalizability, and instability in prolonged learning. Conventional models face challenges in preserving prior knowledge while accommodating new information, hence constraining their efficacy in continuous learning contexts.

The proposed CNN-EWC model mitigates these challenges by maintaining critical parameters via EWC, thereby facilitating knowledge retention and adaptation to new tasks. This approach reduces the need for extensive retraining, enhances generalizability across datasets, and maintains model stability over time. CNN-EWC offers a more efficient, flexible, and dependable deep learning framework for lung cancer diagnosis in practical medical applications. The main contributions of this work are summarized as follows:

- Involved in building effective techniques for lung cancer classification and detection with CNN enhanced with EWC.
- Model designed to tackle the problem of catastrophic forgetting in lifelong deep learning in which serious weights are retained at the time of incremental learning.
- The model was evaluated on histopathological images of cancerous tissues with high accuracy and functionality over varying datasets, proving its readiness for real medical diagnosis.

The remaining sections of the study are organized as follows, In Section 2, the related works are presented, while Section 3 introduces the proposed method. Section 4 presents the results and discussions; Section 5 shows the limitations of the proposed model and Section 6 concludes with a few suggestions for future research.

2 Related works

In the quickly advancing field of medical image analysis, deep learning methodologies, especially CNNs, have shown significant potential in the detection of lung cancer and the enhancement of diagnostic imaging. Several foundational investigations have utilized comprehensive image datasets, with significant research employing large-scale collections of histopathology images to train and validate advanced CNN architectures [19].

For example, the author presented study concentrates on the detection of lung cancer through the application of deep learning techniques, with a particular emphasis on CNNs. CNNs are utilized for the automatic classification and detection of lung cancer in histopathological images, thereby minimizing dependence on manual analysis. The research employs an extensive dataset of histopathological images pertaining to lung cancer. The CNN architecture is designed to extract features and recognize patterns associated with lung cancer. The model for the mentioned study attained an accurate score of 95%, illustrating its capability for precise classification. The findings indicate that CNNs can markedly enhance the early identification of lung cancer. Nonetheless, the limitation of the study highlights the critical role of deep learning in enhancing the efficiency and accuracy of diagnoses performed by pathologists. The manuscript lacks adequate information regarding data preprocessing, augmentation techniques, and computational demands, all of which are critical factors influencing model performance and scalability. The identified factors underscore the necessity for additional validation and refinement of the approach in subsequent research endeavors [20].

Another study investigates the application of ResNet50 architecture, CNN recognized for its efficacy in image classification tasks. The ResNet50 model has been developed to categorize lung cancer into various classifications utilizing histopathological images. The model demonstrated a notable accuracy of 98%, suggesting its capability for precise diagnosis.

The results exhibit certain limitations; external validation across diverse datasets is essential to confirm their applicability in real-world scenarios, the model's performance needs to be assessed in clinical settings to determine its robustness and adaptability to variations in imaging equipment and patient populations [21].

Nayak et al. [22] introduced a method that combines an image preprocessing pipeline with spatial attention mechanisms to enhance the performance of the model. The model employs a neural network architecture (NetB3), which improves its capacity to concentrate on pertinent regions of the image. The model attained a classification accuracy of 99.4%, illustrating its efficacy in identifying lung cancer. Nonetheless, the study's limitations fail to account for potential class imbalances within the dataset, which may impact the accuracy of the model. The absence of information regarding the computational resources necessary for training is noteworthy, as this could pose a limitation for practical applications. Finally, the potential for preventing overfitting has not been addressed, particularly in the absence of external validation or cross-validation on data that has not been previously encountered.

Continuous deep learning, often referred to as continual or lifelong learning, represents a developing area within artificial intelligence. In this domain, models are designed to acquire new tasks incrementally while preserving knowledge from earlier tasks. In contrast to conventional machine learning approaches that typically operate under the assumption of a static dataset, continuous learning effectively tackles situations where data are incrementally accessible over time. Methods such as EWC are effective in addressing catastrophic forgetting, a phenomenon where models tend to lose previously acquired knowledge when exposed to new tasks. The limitations of current approaches include challenges in ensuring models can generalize across diverse tasks and datasets, as well as the difficulty in adapting to rapidly evolving data streams without significant retraining [23].

In 2023, Li and colleagues presented a Continuous learning system (CLS) that utilizes deep learning in conjunction with optimization and ensemble methods to improve accuracy in medical diagnoses. The study employed ultrasound imaging of breast masses, involving 629 masses and 2,235 images from 561 cases, to train the model through 6 stages aimed at differentiating between benign and malignant tumors, as well as recognizing specific pathological types and diseases. The CLS underwent evaluation through the analysis of 7 independent datasets and was benchmarked against the assessments of 21 physicians. At the sixth training stage, the diagnostic performance of the system exceeded that of 20 medical professionals. This innovative approach shows potential for accurate breast mass diagnosis and could be adapted for intelligent diagnostics in other organs, thereby advancing the application of artificial intelligence in precision medicine. However, there are limitations to the study including physicians utilized only one dataset for testing, which comprised only 629 breast masses. Additionally, the diagnostic effectiveness of uncropped images was superior to that of cropped images, but this finding requires multi-center verification [24].

The study in 2023 conducted by Wang and colleagues proposed a novel deep learning model named CoroTrans-CL that was developed for the purpose of recognizing coronavirus infections in CT and chest X-ray images. The model utilizes the Swin Transformer architecture and integrates both regularization-based and rehearsal-based continuous learning strategies. The evaluation of CoroTrans-CL was conducted using the CL-COVID dataset, comprising 954 CT and 470 X-ray images for training, through joint training and continual learning experiments. In the joint training setting, the model attained an accuracy of 95.34% and a precision of 97.18%, demonstrating a performance enhancement of 16–20% compared to alternative models. In the context of continual learning, CoroTrans-CL achieved an accuracy of 83.40%, surpassing other models by roughly 30%. While the results underscore its potential in coronavirus image recognition, its adaptability to other datasets and medical imaging tasks requires further investigation; however, the proposed methodology underwent evaluation utilizing a designated dataset comprising CT and X-ray images pertaining to coronavirus infections. Its efficacy in relation to alternative datasets or different medical imaging applications may exhibit variability. The study does not address the model's ability to generalize across different types of imaging devices or real-world clinical scenarios, where variability in image quality and data distribution might affect its performance [25].

In 2020, a study conducted by Yujiang implemented continuous learning methodologies to enhance forecasting accuracy in regional energy markets. This was achieved utilizing a dataset that included 1 year of 15 min resolution data sourced from 10 renewable energy generators and 10 local consumer plants. The evaluation encompassed methods including Learning without Forgetting, EWC, online-EWC, and synaptic intelligence. The experimental findings indicated that EWC and online-EWC significantly mitigated catastrophic forgetting, ensuring a minimal forgetting ratio. However, these methods increase training time depending on the scenario. Limitation of study is that the experiments are run on data from a small power grid, and the findings of this article can be applied to any level of the power grid where catastrophic forgetting can occur and EWC and online-EWC algorithms, while effective in reducing the forgetting ratio, may increase the training time compared to other algorithms [26].

3 Proposed model

This methodology facilitates the model's ability to acquire new tasks while mitigating the risk of catastrophic forgetting, which is a significant concern in the realm of continuous learning. The Fisher Matrix is employed by the model to determine which parameters are essential for previous tasks, imposing penalties on substantial alterations to those parameters in subsequent training sessions. The proposed model is illustrated in Figure 1.

3.1 Loading lung cancer dataset

The LC25000 datasets [27] are used, which contain five classes of histopathology images (colon and lung cancer), but only three classes for lung cancer are used. There are 5,000 images of lung benign tissue (*n*), 5,000 images of lung adenocarcinoma (ACA), and 5,000 images lung squamous cell carcinoma (SCC), every image in the dataset is in jpeg format and has a resolution of 768 × 768 pixels. Table 1 illustrates the three types of lung cancer that are used in the proposed model.

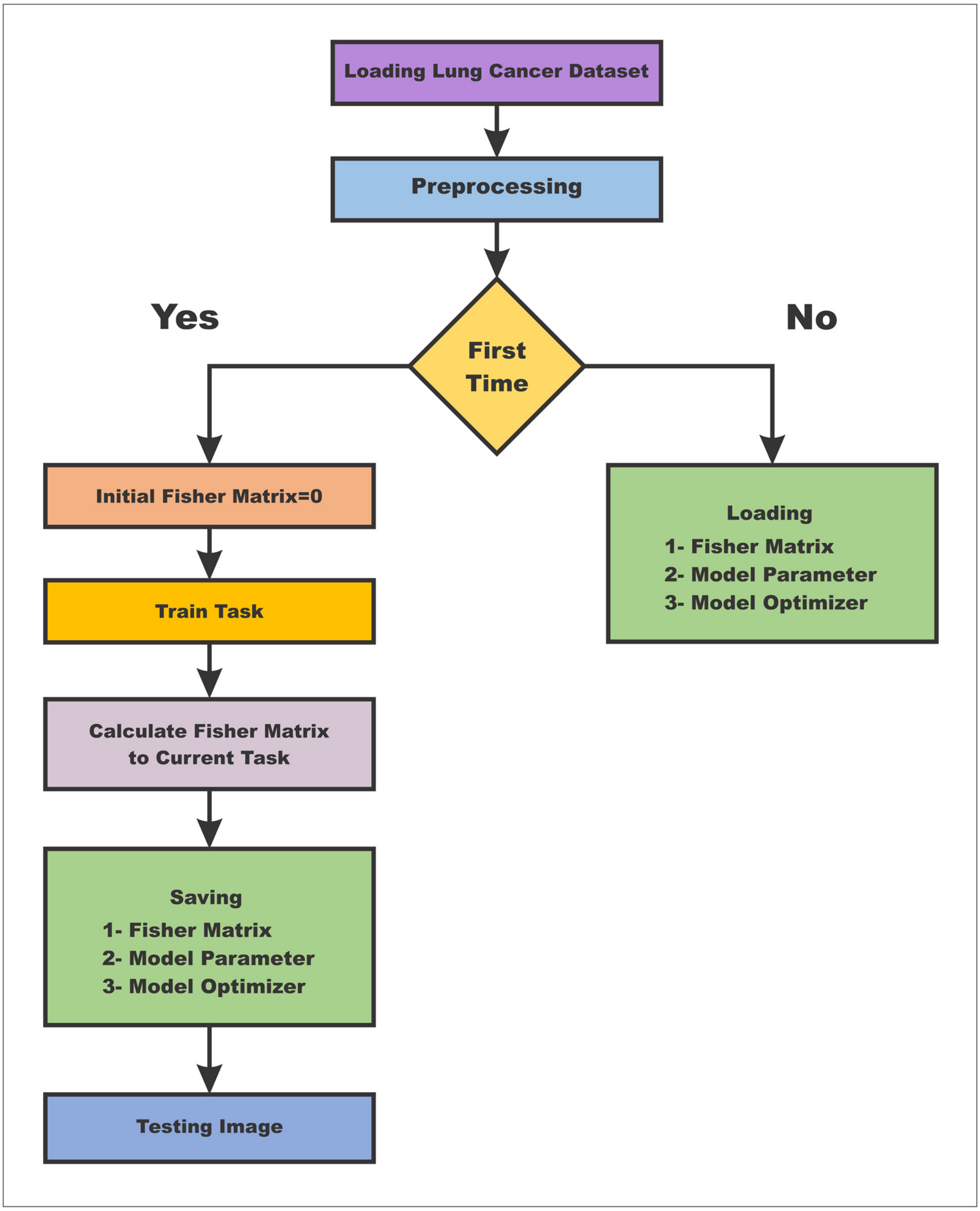
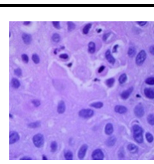
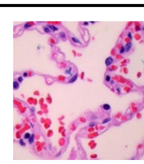
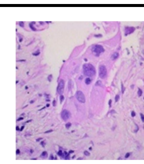


Figure 1: The proposed EWC model. Source: Created by the authors.

Table 1: Cancer type and class name of the used dataset [27]

Cancer type	**SCC**	***n***	**ACA**
Sample image for each type			
Class name	Lung_SCC	Lung_*n*	Lung_ACA
Number of images	5,000 images	5,000 images	5,000 images

3.2 Preprocessing

There are several ways to process the input image data before starting the training process.

1. Resizing: All the input images were resized to 224 × 224), this process reduces errors in the shape during the training process.
2. Convert image to tensor: The images are resized and converted into a shape that suits the training model using a process called To-Tensor and rearranged the data to format (C, H, W), where

- C is the number of channels (3 for RGB images).
- H is the image height.
- W is the image width.

3. Normalizing: the images were normalized until the values were between 0 and 1 to improve convergence during training.

3.3 Training and calculating Fisher matrix

After entering and processing part of lung cancer dataset images, if the data are entered at the first time (Task 1), the value of Fisher Matrix equals to zero (Fisher Matrix is array stored weights and parameters that are trained in the network) because there is no data stored in it, and the processed data are trained using CNN as parameters illustrated in Table 2.

The model architecture is shown in Table 3.

– Initial convolution uses a large 7 × 7 kernel with stride 2
– Subsequent layers use 3 × 3 convolutions
– Down sampling occurs in layers 2, 3, and 4 using 1 × 1 convolutions
– Batch norm applied after each convolution with eps = 1×10^{-5}, momentum = 0.1
– ReLU activation used after Batch Norm
– Final layer uses AdaptiveAvgPool2d to 1 × 1 output
– Final fully connected layer reduces to three output features

Table 2: Hyper parameters of the proposed model

Parameter name	Parameter value	Reason
Epochs	20	Sufficient iterations for learning without undue training duration
Learning rate	0.001	Guarantees consistent updates and avoids surpassing minima
Dropout rate	0.5	Mitigates overfitting by randomly deactivating 50% of neurons
Batch size	64	Achieves a balance between computing efficiency and consistent gradient updates
Training size of data	70%	Supplies adequate data for training while retaining validation data
Validation of data	30%	Facilitates significant assessment without compromising training efficacy
Loss function	Cross-entropy loss	Optimal for multi-class classification situations
Optimizer	SGD	Facilitates generalization and mitigates overfitting, albeit with a slower convergence rate
Activation function	ReLu	Incorporates non-linearity, enhancing the acquisition of intricate patterns

The proposed EWC continuous deep learning model was created on more than one scenario, one of which is entering a set of lung cancer images, and after training and processing them, the results determine whether the person has lung cancer or not and what type that infected, after getting the result stored it and after a period of time a new set of data are entered and trained based on the parameters and weights on which the previous data were trained, and the results are also stored on top of the previous results to retrieve them at a later time, i.e. data continues to arrive at different time periods and all of them are trained according to the

Table 3: CNN architecture

Layer	Input channels	Output channels	Kernal size	Stride	Padding
Conv1	3	64	(7,7)	(2,2)	(3,3)
Layer1 Block 0 conv1	64	64	(3,3)	(1,1)	(1,1)
Layer1 Block 1 conv1	64	64	(3,3)	(1,1)	(1,1)
Layer2 Block 0 conv1	64	128	(3,3)	(2,2)	(1,1)
Layer2 Block 1 conv1	128	128	(3,3)	(1,1)	(1,1)
Layer3 Block 0 conv1	128	256	(3,3)	(2,2)	(1,1)
Layer3 Block 1 conv1	256	256	(3,3)	(1,1)	(1,1)
Layer4 Block 0 conv1	256	512	(3,3)	(2,2)	(1,1)
Layer4 Block 1 conv1	512	512	(3,3)	(1,1)	(1,1)
Fc layer	512	3	—	—	

same weights and parameters, and this ensures the quality of the extracted results in a short time, not as if a very large set of data was trained at one time and then if new data come, they are all trained again, this ensures that the proposed model only trains the new added data.

3.4 Testing images

Several tests were conducted to ensure the validity of the model and that it stores important information about each entered task to be used when a new task comes in. It was tested on a set of images from the first task after training the model on three tasks at different times. In additional tests, a set of images that had not been used during training was utilized to confirm the accuracy and validity of the proposed model. The performance of the proposed model was measured by several metrics, which are accuracy, precision, recall, *f*1-score, and support.

4 Results and discussion

In this section, the results of the proposed model are discussed, in which the dataset was used [27]. 13,500 images were trained at three different times and a different number of images. The obtained results are shown in Table 4.

The results in Table 4 showed that as the quantity of images per class diminishes in later tasks, the performance remains stable. This demonstrates the model's resilience to a decrease in the training samples, particularly for Lung_*n*, which reliably attains perfect or near-perfect outcomes. Also, the model demonstrates exceptional classification performance across tasks, with accuracy increasing over time (98% to 99.4% to 99.6%).

The efficacy of continual learning strategies such as EWC is underscored by the gradual decrease in misclassifications. Finally, the results underscore the effectiveness of EWC in preventing catastrophic forgetting. The model ensures knowledge retention by maintaining high performance on previous tasks, despite the addition of new ones. Figure 2 illustrates the confusion matrix for the proposed model for three tasks.

A lung disease classification system's performance on three separate tests is shown by these confusion matrices. For three lung conditions (lung_ACA, lung_*n*, and lung_SCC), the matrices compare predicted labels to actual diagnoses. With little interactor misclassifications and high diagonal scores (578 for ACA, 621 for normal tissue, and 555 for SCC), the model performed admirably in Task 1. With 430,471, and 431 correct predictions in Task 2, performance is little lower but still respectable. Either the dataset is more difficult, or the model is less successful for this work, since work 3 shows much lower performance across all classes (289, 280, and 324 correct predictions). Overall, the model does very well on Task 1, very well on Task 2, and with less performance on Task 3, but it still manages to classify all three kinds of lung tissue reasonably well.

Table 4: Proposed model results

Number of tasks	Number of classes in each task	Number of images in each class	Precision (%)	Recall (%)	*F*1-score (%)	Support	Accuracy (%)
EWC_TASK1 (6,000 images)	Lung_ACA	2,000	98	95	96	611	98
Training (4,200 images)	Lung_*n*	2,000	100	100	100	621	
Testing (1,800 images)	Lung_SCC	2,000	94	98	96	568	
EWC_TASK2 (4,500 images)	Lung_ACA	1,500	98	98	98	439	99.4
Training (3,150 images)	Lung_*n*	1,500	100	100	100	741	
Testing (1,350 images)	Lung_SCC	1,500	98	98	98	440	
EWC_TASK3 (3,000 images)	Lung_ACA	1,000	100	98	99	295	99.6
Training (2,100 images)	Lung_*n*	1,000	100	100	100	280	
Testing (900 images)	Lung_SCC	1,000	98	100	99	325	

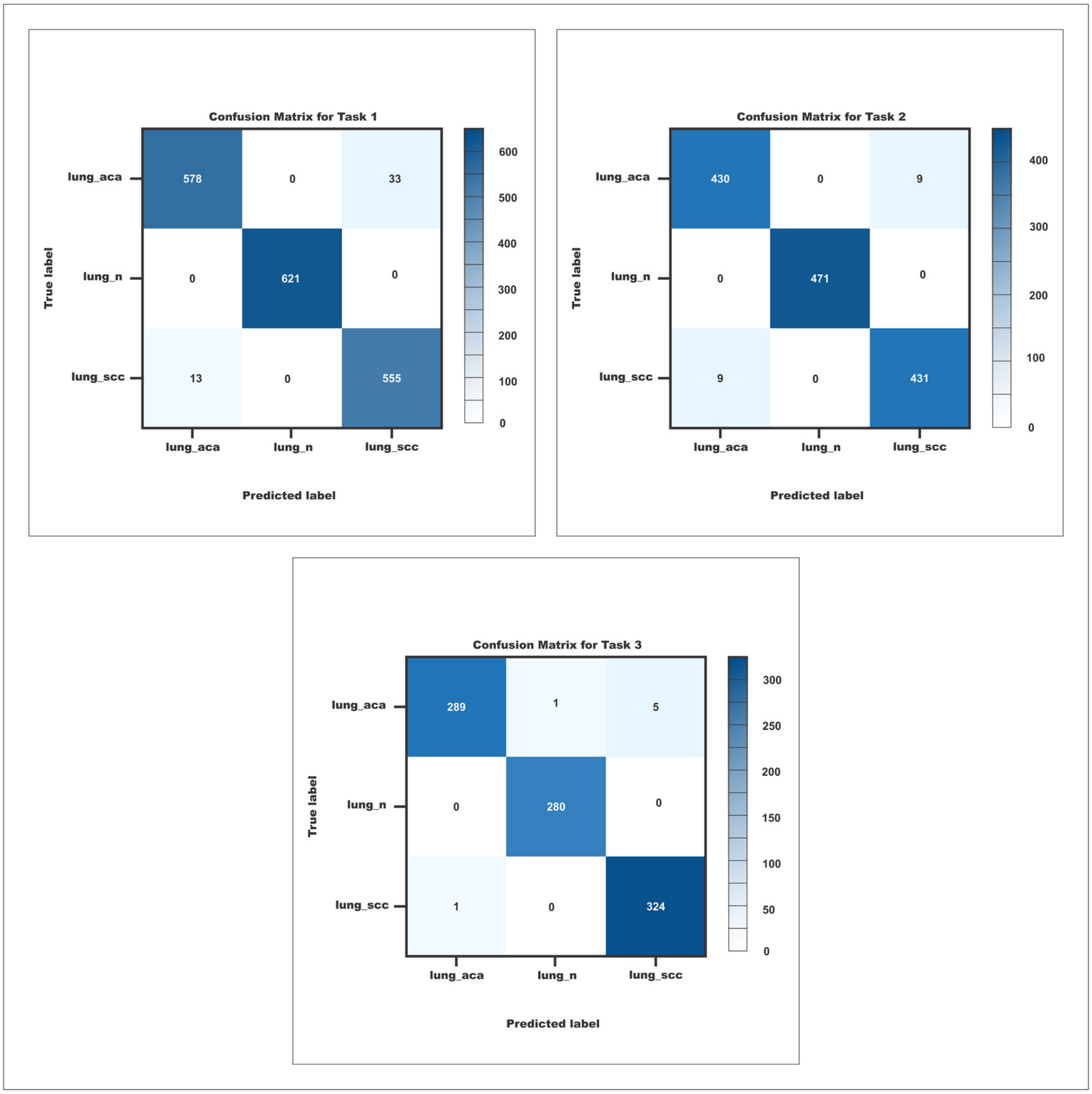


Figure 2: Confusion matrix for the proposed model. Source: Created by the authors.

The results of the accuracy and loss rate are shown in Figure 3.

In the first task, the training was stable at the end, where the hyper parameter (epoch = 20) was determined and the training stopped and was stable at (epoch = 18). Also, the percentage of losses was very small. The scatter in the first task starts from 70 and 98 that it took some time to train because it was the first time, and the number of images was large. Loss in Tasks 2 and 3 is considered good because in the end, it settled and stopped at epoch 18. Finally, the three tasks indicate that training accuracy and validation accuracy are close together, which indicates that the images were trained well.

Additional extra tests were conducted on the model to ensure that the images were classified correctly. Two extra tests were conducted, the first was using 1,500 images that the model had not been trained on, the results obtained are shown in Table 5. For the second one, images were taken from the first task and tested on the final obtained model to ensure that the model worked correctly and recognized the images that were trained on before, the obtained results are shown in Table 6.

The model exhibits significant robustness and accuracy across diverse dataset sizes, reflecting its strong performance in this classification task. Even for lesser datasets (100 or fewer images), accuracy metrics reach a plateau, indicating that large datasets may not be required for this task. Also, the model exhibits effective

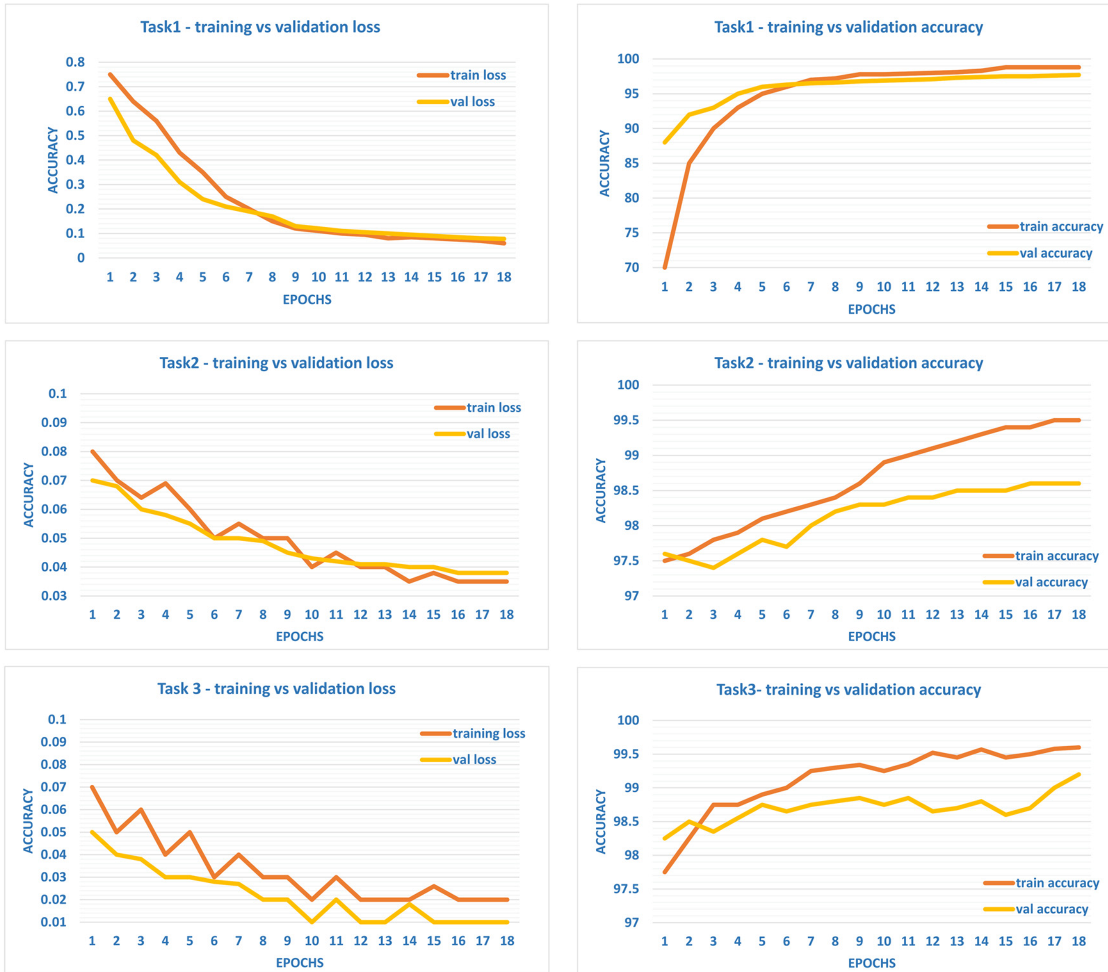


Figure 3: The proposed model's loss and accuracy. Source: Created by the authors.

Table 5: Testing images with the proposed model

Example	Number of images in each class	Result	Accuracy	Time (s)
1,500 images	Lung SCC = 500 jpg image	Lung SCC = 493 jpg image	SCC = 98%	00.16
	Lung *n* = 500 jpg image	Lung *n* = 499 jpg image	*n* = 99%	
	Lung ACA = 500 jpg image	Lung ACA = 500 jpg image	ACA = 100%	
900 images	Lung SCC = 300 jpg image	Lung SCC = 300jpg image	SCC = 100%	00.06
	Lung *n* = 300 jpg image	Lung *n* = 300 jpg image	*n* = 100%	
	Lung ACA = 300 jpg image	Lung ACA = 294 jpg image	ACA = 0.98%	
300 images	Lung SCC = 100 jpg image	Lung SCC = 100 jpg image	SCC = 100%	00.03
	Lung *n* = 100 jpg image	Lung *n* = 100 jpg image	*n* = 100%	
	Lung ACA = 100 jpg image	Lung ACA = 99 jpg image	ACA = 99%	
100 images	Lung SCC = 36 jpg image	Lung SCC = 36 jpg image	SCC = 100%	00.00
	Lung *n* = 30 jpg image	Lung *n* = 30 jpg image	*n* = 100%	
	Lung ACA = 34 jpg image	Lung ACA = 33 jpg image	ACA = 99%	
10 images	Lung SCC = 3 jpg image	Lung SCC = 3 jpg image	SCC = 100%	00.00
	Lung *n* = 4 jpg image	Lung *n* = 4 jpg image	*n* = 100%	
	Lung ACA = 3 jpg image	Lung ACA = 3 jpg image	ACA = 100%	
3 images	Lung SCC = 1 jpg image	Lung SCC = 1 jpg image	SCC = 100%	00.00
	Lung *n* = 1 jpg image	Lung *n* = 1jpg image	*n* = 100%	
	Lung ACA = 1 jpg image	Lung ACA = 1 jpg image	ACA = 100%	

Table 6: Testing images from Task 1 with the proposed model

Example	Number of images in each class	Result	Accuracy	Time (s)
100 images	Lung SCC = 33 jpg image Lung *n* = 34 jpg image Lung ACA = 34 jpg image	Lung SCC = 33 jpg image Lung *n* = 34 jpg image Lung ACA = 34 jpg image	SCC = 100% *n* = 100% ACA = 100%	00.01

scalability with dataset size, attaining expedited processing times for smaller datasets without compromising accuracy.

The processing duration diminishes with a decrease in the number of images, varying from 0.16 s for 1,500 images to nearly 0 for 10 and 3 images. Finally, Lung ACA exhibits minor fluctuations, demonstrating near-perfect yet not absolute accuracy for extensive datasets.

The model exhibits impeccable performance, achieved completeness in all three categories. This suggests that the model demonstrates a significant level of efficacy for this dataset. The equitable distribution of images across the various classes may have played a significant role in achieving this elevated accuracy, given that no individual class predominates within the dataset. The classification process occurs at an impressive speed of 0.01 s, making it highly suitable for real-time applications.

Finally, a comparison with previous works is shown in Table 7, at which the CNN-EWC model attains impressive accuracy of 99.6%, illustrating its superiority compared to alternative methods for this classification task and the models demonstrate a steady enhancement in accuracy as they evolve from conventional deep neural networks (DNNs) to advanced architectures such as ResNet50, NetB3, and CNN-EWC.

Table 7: Comparison with previous research

Reference number	Method	Accuracy (%)
[20]	DNN	95
[21]	ResNet50 in CNN	98
[22]	NetB3	99.4
The proposed model	CNN-EWC	99.6

5 Limitations of the proposed model

Current deep learning models for lung cancer diagnosis encounter significant obstacles, such as catastrophic forgetting, reliance on extensive annotated datasets, inadequate generalizability, and instability in prolonged learning. Conventional models face challenges in preserving prior knowledge while accommodating new information, hence constraining their efficacy in continuous learning contexts.

6 Conclusion and future work

The proposed CNN-EWC model has demonstrated continuous deep learning effectively with the ability to correctly classify images based on the dataset that the model was trained on at different time points. This work is based on providing a suitable image classification model that can classify correct images with high classification efficiency.

Contemporary deep learning models for lung cancer diagnosis encounter obstacles like catastrophic forgetting, dependence on extensive annotated datasets, restricted generalizability, and instability over extended learning periods. These constraints impede their efficacy in continuous learning applications. The proposed CNN-EWC model addresses these concerns by maintaining essential parameters and improving flexibility; nonetheless, additional validation is required to confirm its resilience across various medical datasets.

The research contributions for EWC algorithm were used to preserve important information that can be trained on later. In creating the deep learning model, the CNN algorithm is used to extract features, while the EWC algorithm is used to store parameters. It also eliminates the time problem.

The presented contribution is a CNN model with very high classification accuracy that enables the extraction of the most important image features to the level of 99.6%. This work requires entering a set of image data from time to time and training the model on it and extracting important information from the images and storing it and then retrieving it when other data arrive.

In this study, the practical advantage of the model was tested on a set of images that the model was trained on for the first time and the results were very high, reaching 100%, and it was tested on images that the model was not trained on and achieved high performance as it reached 100%.

Finally, the principle of continuous learning using the EWC method has proven its effectiveness in continuous training in terms of accuracy, speed, saving time, and correct classification of images.

Future work investigating the expansion of the suggested CNN-EWC architecture should accommodate more intricate multi-task scenarios including additional cancer kinds and larger datasets. Furthermore, including additional continual learning methodologies may further improve adaptability and efficacy in practical clinical application.

Funding information: The authors state no funding involved.

Author contributions: Zainab Muhammed designed the methodology, designed the software, performed the experiments, reviewed the collected data, and made the initial analysis and writing. Belal Al-Khateeb oversaw the study, developed the research idea, and helped interpret the data, facilitated project administration and provided key resources, and approved the final manuscript.

Conflicts of interest: The authors state no conflict of interest.

Ethical approval: This study does not involve humans, animals, or sensitive data that require ethical approval.

Data availability statement: The datasets and materials supporting this study will be available from the corresponding author on reasonable request.

References

[1] Liu T, Siegel E, Shen D. Deep learning and medical image analysis for COVID-19 diagnosis and prediction. Annu Rev Biomed Eng. 2022;24(1):179–201. doi: 10.1146/annurev-bioeng-110220-012203.

[2] Rajpurkar P, Irvin J, Zhu K, Yang B, Mehta H, Duan T. CheXNet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv (Cornell University). 2017. doi: 10.48550/arxiv.1711.05225.

[3] Wang L, Yin Y, Glampson B, Peach R, Barahona M, Delaney BC, et al. Transformer-based deep learning model for the diagnosis of suspected lung cancer in primary care based on electronic health record data. EbioMedicine. 2024;110:105442. doi: 10.1016/j.ebiom.2024.105442.

[4] Zuo W, Zhou F, Li Z, Wang L, Zhang Y, Chen M. Multi-resolution CNN and knowledge transfer for candidate classification in lung nodule detection. IEEE Access. 2019;7:32510–21. doi: 10.1109/ACCESS.2019.2903587.

[5] Gao C, Wu L, Wu W, Huang Y, Wang X, SunZ, et al. Deep learning in pulmonary nodule detection and segmentation: a systematic review. Eur Radiol. 2024;35:255–66. doi: 10.1007/s00330-024-10907-0.

[6] Topol EJ. Deep medicine: How artificial intelligence can revolutionize healthcare. Basic Books; 2022.

[7] Selvikvåg Lundervold A, Lundervold A. An overview of deep learning in medical imaging focusing on MRI. Z Med Phys. 2019;29(2):102–27. doi: 10.1016/j.zemedi.2018.11.002.

[8] Hong GS, Jang M, Kyung S, Cho K, Jeong J, Lee GY, et al. Overcoming the challenges in the development and implementation of artificial intelligence in radiology: a comprehensive review of solutions beyond supervised learning. Korean J Radiol. 2023;24(11):1061–80. doi: 10.3348/kjr.2023.0393.
[9] Kirkpatrick J, Pascanu R, Rabinowitz N, Veness J, Desjardins G, Rusu AA, et al. Overcoming catastrophic forgetting in neural networks. Proc Natl Acad Sci. 2017;114(13):3521–6. doi: 10.1073/pnas.1611835114.
[10] Hadsell R, Rao D, Rusu AA, Pascanu R, Smith M, Johnson L, et al. Embracing change: continual learning in deep neural networks. Trends Cognit Sci. 2020;24(12):1028–40. doi: 10.1016/j.tics.2020.09.004.
[11] Aich A. Elastic weight consolidation (EWC): Nuts and bolts. arXiv preprint arXiv:2105.04093v1. 2021. https://arxiv.org/abs/2105.04093v1.
[12] Wang L, Zhang X, Su H, Zhu J. A comprehensive survey of continual learning: theory, method and application. IEEE Trans Pattern Anal Mach Intell. 2024;46(8):5362–83, https://ieeexplore.ieee.org/document/10444954.
[13] Parisi GI, Tani J, Weber C, Wermter S. Lifelong learning of human actions with deep neural network self-organization. Neural Netw. 2017;96:137–49. doi: 10.1016/j.neunet.2017.09.001.
[14] Kutalev A, Lapina A. Stabilizing elastic weight consolidation method in practical ML tasks and using weight importances for neural network pruning. arXiv preprint arXiv:2109.10021. 2021. https://arxiv.org/abs/2109.10021.
[15] Kumari P, Chauhan J, Bozorgpour A, Huang B, Azad R, Merhof D. Continual learning in medical imaging analysis: a comprehensive review of recent advancements and future prospects. arXiv preprint arXiv:2312.17004. 2023. doi: 10.48550/arxiv.2312.17004.
[16] Huszár F. Note on the quadratic penalties in elastic weight consolidation. Proc Natl Acad Sci USA. 2018;115(11):2539–665. doi: 10.1073/pnas.1717042115.
[17] Abiodun OI, Jantan A, Omolara AE, Dada KV, Umar AM, Linus OU. Comprehensive review of artificial neural network applications to pattern recognition. IEEE Access. 2019;7:158820–46. doi: 10.1109/ACCESS.2019.2945545.
[18] Mundt M, Hong Y, Pliushch I, Ramesh V. A wholistic view of continual learning with deep neural networks: forgotten lessons and the bridge to active and open world learning. Neural Netw. 2023;160:306–36. doi: 10.1016/j.neunet.2023.01.014.
[19] Crasta LJ, Neema R, PaisAR. A novel deep learning architecture for lung cancer detection and diagnosis from computed tomography image analysis. Healthcare Anal. 20245100316doi: 10.1016/j.health.2024.100316.
[20] Mohalder RD, Hossain KA, Sarkar JP, Paul L, Raihan M, Talukder KH. Lung cancer detection from histopathological images using deep learning. In Machine Intelligence and Emerging Technologies, vol. 490, Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering; 2023. p. 201–12. doi: 10.1007/978-3-031-34619-4_17.
[21] Khatun MF, Ajmain MR, Assaduzzaman M. A deep learning approach to detect and classification of lung cancer. International Conference for Advancement in Technology (ICONAT); 2023. p. 1–6. doi: 10.1109/ICONAT57137.2023.10080801.
[22] Nayak T, Gokulkrishnan N, Chadaga K, Sampathila N, Mayrose H, Swathi KS. Automated histopathological detection and classification of lung cancer with an image pre-processing pipeline and spatial attention with deep neural networks. Cogent Eng. 2024;11(1):2357182. doi: 10.1080/23311916.2024.2357182.
[23] Parisi GI, Kemker R, Part JL, Kanan C, Wermter S. Continual lifelong learning with neural networks: a review. Neural Netw. 2019;113:54–71. doi: 10.1016/j.neunet.2019.01.012.
[24] Li J, Jin L, Wang Z, Cao Y, Peng Q, Luo J. Towards precision medicine based on a continuous deep learning optimization and ensemble approach. NPJ Digital Med. 2023;6(1):18. doi: 10.1038/s41746-023-00759-1.
[25] Wang B, Zhang D, Tian Z. CoroTrans-CL: A novel transformer-based continual deep learning model for image recognition of coronavirus infections. Electronics. 2023;12(4):866. doi: 10.3390/electronics12040866.
[26] He Y, Henze J, Sick B. Continuous learning of deep neural networks to improve forecasts for regional energy markets. IFAC-PapersOnLine. 2020;53(2):12175–82. doi: 10.1016/j.ifacol.2020.12.1017.
[27] Talukder MA, Islam MM, Uddin MA, Akhter A, Hasan KF, Moni MA. Machine learning-based lung and colon cancer detection using deep feature extraction and ensemble learning. Expert Syst Appl. 2022;205:117695. doi: 10.1016/j.eswa.2022.117695.