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Development of one channel-football formation neural network (OC-FFNet) for classification the breast ultrasound images

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ABSTRACT

Background: Breast cancer is a leading global health issue, with increasing incidence and mortality rates. In Thailand, it is the most common cancer among women, highlighting the need for better diagnostic methods. Traditional imaging techniques like mammography and ultrasound have limitations that hinder early detection. Recent advances in artificial intelligence (AI), particularly convolutional neural networks (CNNs), offer promising solutions for enhancing breast cancer detection in ultrasound images.

Objective: This study aims to develop a one-channel AI model for detecting breast cancer in ultrasound images, inspired by football formations to structure the CNN layers.

Materials and methods: The dataset comprises 18,000 breast ultrasound images categorized into normal, malignant, and benign cases. Data preprocessing involved image resizing, enhancement, and augmentation to address class imbalances. The proposed AI model, the One-Channel Football Formation Neural Network (OC-FFNet), was designed based on four distinct football formations: 4-3-3, 4-2-3-1, 4-4-2, and 5-4-1. Each formation guided the structuring of CNN layers, incorporating DenseNet-based modified dense blocks and transition layers. Model training was conducted with batch sizes ranging from 64 to 256 and epochs between 50 and 150. Performance evaluation metrics included accuracy, precision, recall, specificity, F1-score, false positive rate, and area under the curve (AUC).

Results: The models based on the 4-3-3 and 4-4-2 formations exhibited the highest classification performance, achieving an accuracy of 0.999, precision of 0.999, recall of 1.000, specificity of 0.999, F1-score of 0.999, and AUC of 0.999. The 4-2-3-1 model attained an accuracy of 0.963, while the 5-4-1 model achieved an accuracy of 0.968. Prediction times were consistent across all models, indicating computational efficiency. The findings suggest that formations with balanced positional distributions, such as 4-3-3 and 4-4-2, required fewer training iterations and larger batch sizes to achieve optimal performance.

Conclusion: The integration of football formation strategies into CNN architecture represents a novel approach to AI model design. The results indicate that strategically structured CNNs can improve breast cancer detection in ultrasound images.

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Introduction

Breast cancer represents significant global health concern, with its incidence and mortality rates escalating in numerous countries. In 2022, the World Health Organization (WHO) reported approximately 2.3 million new cases of breast cancer worldwide, resulting in 670,000 deaths.[1] This malignancy has now surpassed lung cancer as the most diagnosed cancer globally. The rising trend underscores the imperative for enhanced awareness, early detection, and comprehensive management strategies to mitigate the disease's impact.

In Thailand, breast cancer has emerged as the most prevalent cancer among women. The National Cancer Institute reported over 140,000 new cancer diagnoses in 2022, with breast cancer accounting for a substantial proportion of these cases. The annual incidence rate stands at 37.8 per 100,000 population, equating to approximately 22,158 new cases in 2020, which constituted 22.8% of all female cancer cases. This upward trajectory in breast cancer incidence necessitates targeted public health interventions and resource allocation to address the burgeoning burden effectively.[2]

Diagnostic modalities for breast cancer primarily include mammography and breast ultrasound.[3] Mammography, while considered the gold standard, exhibits reduced sensitivity in women with dense breast tissue, potentially leading to false-negative results and delayed diagnoses. Such delays can exacerbate disease progression and complicate treatment outcomes. Moreover, mammography involves exposure to ionizing radiation and requires breast compression, which may cause discomfort and deter some women from participating in regular screening programs. These limitations highlight the need for alternative or adjunctive imaging techniques to improve diagnostic accuracy and patient compliance.[4]

Breast ultrasound serves as a complementary diagnostic tool, particularly advantageous in detecting malignancies obscured in dense breast tissue that mammography might miss. Its non-invasive nature and absence of radiation exposure make it a favorable option for many patients. However, ultrasound is operator-dependent, and its efficacy can vary based on the technician's expertise. Integrating ultrasound into routine screening, especially for high-risk populations, could enhance early detection rates and improve prognostic outcomes.[3,4]

In recent years, artificial intelligence has been increasingly developed and applied to support medical diagnosis, particularly using convolutional neural networks, which are known for their powerful image analysis capabilities. Convolutional neural networks consist of multiple layers designed to extract hierarchical features from input data, enabling high accuracy in complex pattern recognition tasks.[5-10] Notably, the research team observed that the layered structure of convolutional neural networks bears a conceptual similarity to football formations, where each layer corresponds to specific positional roles such as goalkeeper, defender, midfielder, and forward.[11] This analogy provides a novel perspective on designing artificial intelligence architectures by aligning neural network layers with strategic football positions, thereby enhancing interpretability and potential model optimization.

For example, the widely recognized 4-4-2 football formation,[11-14] which comprises four defenders, four midfielders, and two forwards, can be mapped to the layers of a convolutional neural network as follows: four layers in the defense block, four layers in the middle block, and two layers in the forward block (Figure 1). This mapping is not merely conceptual but is strategically employed to organize the neural network layers to emulate hierarchical decision-making processes akin to positional roles on a football field. Such an approach aids in the systematic construction of convolutional neural networks, where each block is tailored to extract features relevant to specific tasks, thus enhancing the model's learning and predictive performance.

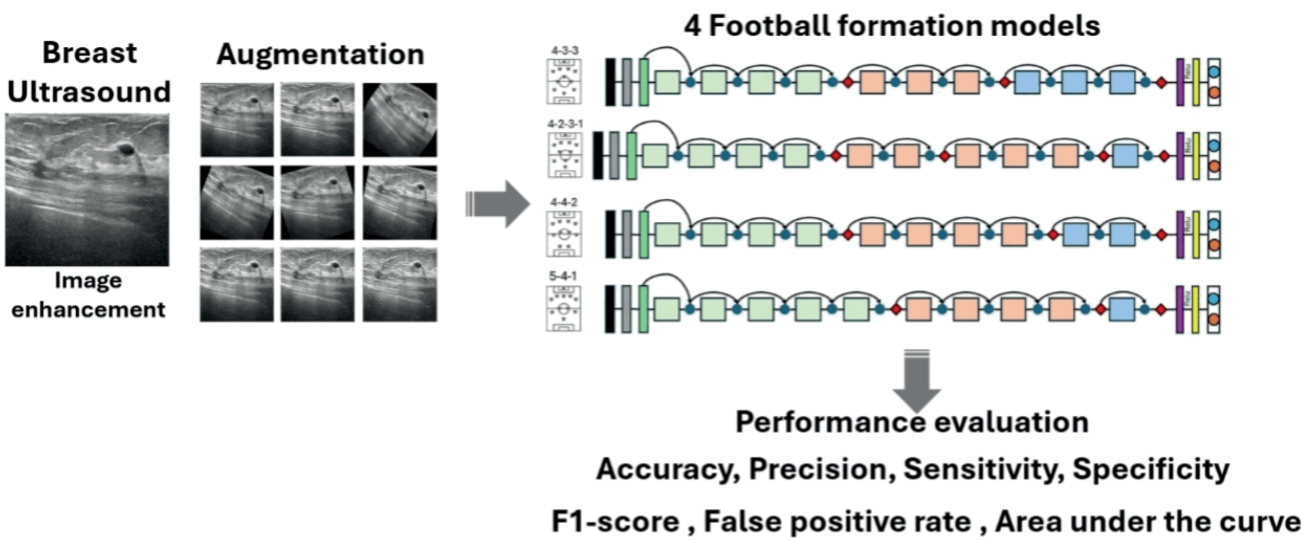

***Figure 1**. Workflows of this study.*

Additionally, the research team is investigating other football formations, encompassing both offensive and defensive strategies, to evaluate the efficacy of these architectural analogies in breast cancer detection. By experimenting with varied formations, such as 4-3-3 for more aggressive feature extraction or 5-4-1 for robust defensive classification layers, the research aims to identify optimal configurations that balance sensitivity and specificity in diagnostic outcomes.[12-14] This exploration of diverse configurations may reveal insights into the most effective architectures for accurate and efficient breast cancer detection using ultrasound images. The strategic alignment of football formations with neural network layers thus not only facilitates conceptualization but also serves as a foundation for optimizing artificial intelligence model structures for medical imaging applications.[15-17]

The primary objective of ongoing research is to develop a one-channel artificial intelligence model tailored for breast cancer detection in ultrasound imagery. This model aims to accurately differentiate between normal and abnormal breast tissues by emulating the strategic organization inherent in football formations. By leveraging artificial intelligence's analytical prowess, this approach aspires to enhance diagnostic precision, facilitate early intervention, and ultimately improve patient outcomes in breast cancer care.

Materials and methods

Data collection

The images utilized in this study were obtained from the online database Kaggle.com. All images were confirmed to be breast ultrasound scans and categorized into three groups: normal breast tissue, malignant tumors, and benign tumors. The dataset consisted of images collected from female patients aged 25 to 75 years. Each image had an average resolution of 500 × 500 pixels and was stored in PNG format. A total of 9,282 breast ultrasound images were sourced from two Kaggle databases,[18-19] with permission granted by the data owners for unrestricted use, eliminating the need for additional consent. The dataset comprised 266 images of normal breast tissue and 9,016 images of abnormal breast tissue, including both malignant and benign tumors.

Inclusion criteria

The study included single breast ultrasound images that were confirmed to depict either normal breast tissue or abnormal breast tissue, including malignant and benign tumors.

Exclusion criteria

Images diagnosed with pathological conditions unrelated to breast masses were excluded from the study to maintain dataset specificity.

To ensure uniformity, all selected images were resized to a consistent matrix size. Image enhancement and noise reduction techniques were subsequently applied to improve image quality and ensure suitability for breast tissue classification.

To address class imbalance and enhance the robustness of the artificial intelligence model, image augmentation techniques were applied to both normal and abnormal breast ultrasound images. Augmentation methods included rotation, translation, and zooming. This approach generated an equal number of images across classes, resulting in 9,000 images of normal breast tissue and 9,000 images of abnormal breast tissue, for a total of 18,000 images.

The dataset was divided into three subsets as follows:

- *Training set*: 70% of the images (12,600 images) were used to train the artificial intelligence model.
- *Validation set*: 20% of the images (3,600 images) were allocated for model validation to optimize hyperparameters and prevent overfitting.
- *Testing set*: 10% of the images (1,800 images) were reserved for evaluating the model's performance and generalization capability.

Development of the football formation-based artificial intelligence model

Concept and design

The proposed artificial intelligence model was developed using a one-channel convolutional neural network architecture, with its internal structure based on DenseNet.[20] The model design was inspired by football formations, categorized into offensive and defensive strategies. Four football formations were selected for implementation:

Attacking formations:

4-3-3 and 4-2-3-1: These formations are recognized as highly effective offensive strategies and are widely adopted by top-tier football clubs such as Manchester City, Real Madrid, Liverpool, and Bayern Munich.

Defensive formations:

5-4-1 and 4-4-2: These formations are well-established defensive strategies commonly employed by elite football clubs, including Manchester City, Real Madrid, and Liverpool.

Architecture of the one-channel football formation neural network (OC-FFNet)

The one-channel football formation neural network (OC-FFNet) was designed to align with football formations, where the number of blocks within the network corresponded to the number of players in each position. The architecture was primarily based on DenseNet, incorporating dense blocks and concatenation layers to enhance feature propagation and reuse.[20]

Key components of dense block

The fundamental components of dense block include:

1. Batch normalization
2. Activation function
3. Convolutional layer
4. Concatenation layer

Modified dense block structure in OC-FFNet

Each modified dense block in the OC-FFNet consists of six layers:

1. Batch normalization
2. ReLU activation function
3. Convolutional layer
4. Batch normalization
5. ReLU activation function
6. Convolutional layer

Transition layers

At the initial stage of the model, the architecture comprises an input layer, convolutional layers, and max pooling layers. Between each position block, transition layers are incorporated to facilitate information flow. Each transition layer consists of:

1. Batch normalization
2. Convolutional layer
3. Average pooling

Final processing layers

Before producing the final model output, the following layers are included:

1. Global average pooling layer
2. Flatten layer
3. Softmax function

Football formation-based network structure

The number of blocks within different sections of the network was determined based on each football formation (Further details are provided in Figure 2):

4-3-3 Formation: 4 Defensive blocks, 3 Midfield blocks, 3 Forward blocks

4-2-3-1 Formation: 4 Defensive blocks, 2 Defensive midfield blocks, 3 Attacking midfield blocks, 1 Forward block

5-4-1 Formation: 5 Defensive blocks, 4 Midfield blocks, 1 Forward block

4-4-2 Formation: 4 Defensive blocks, 4 Midfield blocks, 2 Forward blocks

Each model was trained using batch sizes ranging from 64 to 256, with the number of training epochs varied between 50 and 150.

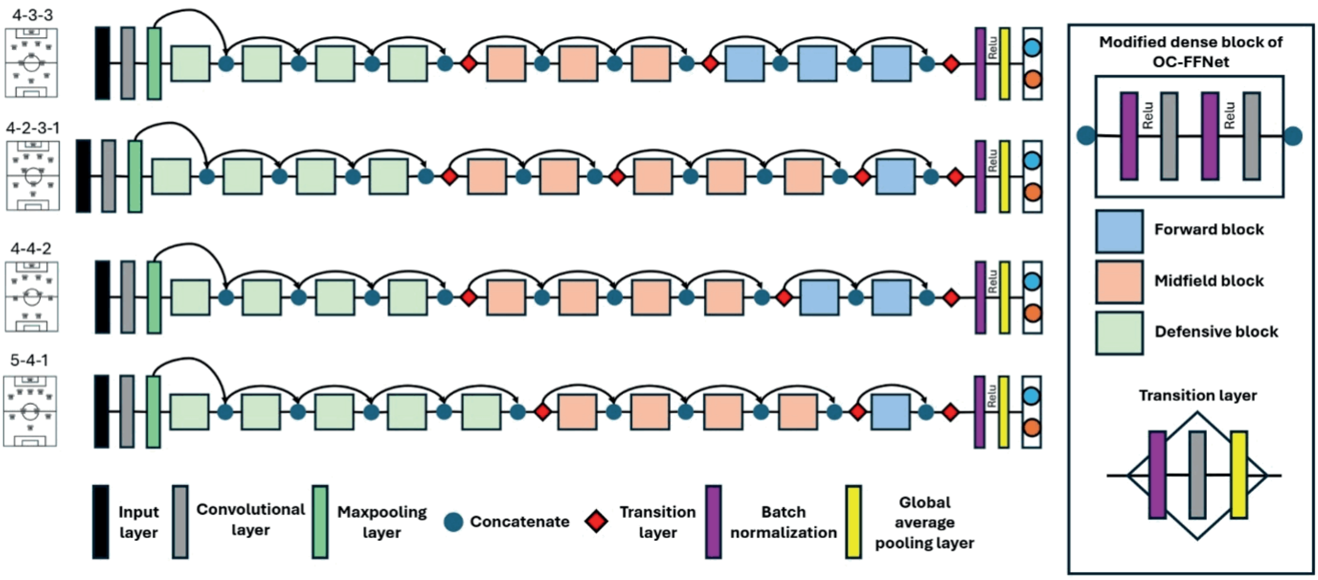

***Figure 2**. illustrates the structure of four football formation networks, the structure of a modified dense block in OC-FFNet and the transition layer in OC-FFNet.*

Performance evaluation

The models' performance in detecting breast cancer in ultrasound images was evaluated using a confusion matrix. The classification outcomes were defined as follows:

True positives (TP): The model correctly identifies and classifies breast cancer in ultrasound images.

True negatives (TN): The model correctly identifies normal images without misclassifying them as cancerous.

False positives (FP): The model incorrectly detects breast cancer in a normal image or misclassifies a benign lesion.

False negatives (FN): The model fails to detect breast cancer in an image that contains a malignant tumor.

To assess model performance, the following metrics were calculated: accuracy, precision (positive predictive value), sensitivity (recall), specificity, F1-score, false positive rate (FPR), and area under the curve (AUC).

Results

Evaluation of the performance of four football formation models

Tables 1 to 2 present the performance evaluation of artificial intelligence models developed using four football formations: 4-3-3, 4-2-3-1, 4-4-2, and 5-4-1. These models were evaluated using various batch sizes ranging from 64 to 256 and training epochs ranging from 50 to 150. The performance metrics included accuracy, positive predictive value (precision), sensitivity (recall), specificity, F-1 score, false positive rate, and the area under the curve. Additionally, the prediction time for 1,800 test images was recorded.

The 4-3-3 formation model exhibited optimal performance with a batch size of 128 and 100 epochs. It obtained an accuracy of 0.999, a precision of 0.999, a sensitivity of 1.000, a specificity of 0.999, an F-1 score of 0.999, a false positive rate of 0.001, and an AUC of 0.999. The prediction time for this model was 6.588 seconds. The 4-2-3-1 formation model demonstrated optimal performance using a batch size of 64 and 150 epochs. It achieved an accuracy of 0.963, a precision of 0.927, a sensitivity of 1.000, a specificity of 0.932, an F-1 score of 0.962, a false positive rate of 0.068, and an AUC of 0.963. The prediction time for this model was 5.122 seconds, as shown in Table 1.

Table 1. The performance of attacking formations (4-3-3 and 4-2-3-1 football formation models)

	Batch size	Epoch	Accuracy	Precision	Sensitivity	Specificity	F1-score	False positive rate	AUC	time (sec)
4-3-3	64	50	0.500	1.000	0.500	0.000	0.667	0.000	0.500	5.044
		100	0.998	0.997	1.000	0.997	0.998	0.003	0.998	4.918
		150	0.967	1.000	0.939	1.000	0.968	0.000	0.967	4.956
	128	50	0.500	1.000	0.500	0.000	0.667	0.000	0.500	6.329
		100	**0.999**	**0.999**	**1.000**	**0.999**	**0.999**	**0.001**	**0.999**	**6.588**
		150	0.803	0.606	1.000	0.717	0.754	0.283	0.803	4.917
	256	50	0.500	1.000	0.500	0.000	0.667	0.000	0.500	6.360
		100	0.500	1.000	0.500	0.000	0.667	0.000	0.500	6.660
		150	0.988	0.977	1.000	0.977	0.988	0.228	0.988	4.701
4-2-3-1	64	50	0.547	0.853	0.529	0.621	0.653	0.379	0.547	5.102
		100	0.850	0.966	0.784	0.955	0.866	0.045	0.850	5.088
		150	**0.963**	**0.927**	**1.000**	**0.932**	**0.962**	**0.068**	**0.963**	**5.122**
	128	50	0.762	0.523	1.000	0.677	0.687	0.323	0.762	4.943
		100	0.545	1.000	0.524	1.000	0.678	0.000	0.545	4.871
		150	0.937	0.880	0.993	0.892	0.933	0.108	0.937	4.940
	256	50	0.788	0.577	1.000	0.703	0.732	0.297	0.788	4.935
		100	0.500	0.000	0.000	0.500	0.000	0.500	0.500	5.189
		150	0.928	0.857	1.000	0.875	0.923	0.125	0.928	4.962

The 5-4-1 formation model achieved its best performance using a batch size of 64 and 150 epochs. It recorded an accuracy of 0.968, a precision of 0.994, a sensitivity of 0.945, a specificity of 0.994, an F-1 score of 0.969, a false positive rate of 0.006, and an AUC of 0.968. The prediction time for the test images was 5.327 seconds. The 4-4-2 formation model demonstrated the highest performance using a batch size of 128 and 100 epochs. Specifically, it achieved an accuracy of 0.999, a precision of 0.999, a sensitivity of 1.000, a specificity of 0.999, an F-1 score of 0.999, a false positive rate of 0.001, and an AUC of 0.999. The prediction time for the test images was 6.647 seconds, as shown in Table 2.

The models based on the 4-4-2 and 4-3-3 formations exhibited the highest accuracy and AUC values, indicating superior predictive performance. The 4-2-3-1 model also demonstrated strong performance, although its specificity and false positive rate were comparatively lower. In contrast, the 5-4-1 formation model showed slightly lower accuracy and AUC metrics. Notably, the consistency in prediction times across most models suggests that computational efficiency was maintained regardless of the formation strategy employed. However, the faster prediction time of the 4-2-3-1 model warrants further investigation to understand the underlying factors contributing to this difference.

Table 2. The performance of defensive formations (5-4-1 and 4-4-2 football formation models)

	Batch size	Epoch	Accuracy	Precision	Sensitivity	Specificity	F1-score	False positive rate	AUC	Time (sec)
5-4-1	64	50	0.609	0.894	0.569	0.754	0.696	0.246	0.609	5.410
		100	0.529	1.000	0.515	1.000	0.680	0.000	0.529	5.400
		150	**0.968**	**0.994**	**0.945**	**0.994**	**0.969**	**0.006**	**0.968**	**5.327**
	128	50	0.500	1.000	0.500	0.000	0.667	0.000	0.500	9.030
		100	0.967	0.933	1.000	0.938	0.966	0.063	0.967	5.405
		150	0.912	0.823	1.000	0.850	0.903	0.150	0.912	5.353
	256	50	0.548	0.963	0.526	0.783	0.681	0.217	0.548	5.276
		100	0.726	0.979	0.650	0.957	0.781	0.043	0.726	5.189
		150	0.756	0.511	1.000	0.672	0.677	0.328	0.756	5.267
4-2-2	64	50	0.495	0.990	0.497	0.000	0.662	1.000	0.495	5.415
		100	0.994	0.999	1.000	0.999	0.999	0.001	0.999	5.928
		150	0.497	0.996	0.499	0.000	0.665	1.000	0.498	5.196
	128	50	0.751	0.917	0.688	0.875	0.786	0.125	0.751	6.706
		100	**0.999**	**0.999**	**1.000**	**0.999**	**0.999**	**0.001**	**0.999**	**6.647**
		150	0.980	0.999	0.963	0.999	0.980	0.001	0.980	6.635
	256	50	0.500	1.000	0.500	0.000	0.667	0.000	0.500	5.089
		100	0.500	1.000	0.500	0.000	0.667	0.000	0.500	5.033
		150	0.500	1.000	0.500	0.000	0.667	0.000	0.500	6.723

Discussion

This study introduces a novel approach to artificial intelligence model development, representing the first instance in which football formation strategies have been utilized as a structural basis for designing and constructing convolutional neural network architectures. By analyzing the spatial arrangement of football formations, the research team identified the interconnected positioning of players within various tactical strategies. This observation led to the hypothesis that the number of players in each position could be mapped onto the number of layers used for feature extraction in the hidden layers of the convolutional neural network model.

In football strategy planning, coaches select formations based on their emphasis on either offensive or defensive play. Tactical formations have evolved significantly over time. During the 20th century, the 5-3-2 formation was predominantly employed for defensive strategies, whereas the 4-2-4 formation gained prominence in the 1950s for its offensive effectiveness, achieving considerable success during that period[13]. In contemporary football, formations such as 4-3-3, 4-4-2, and 3-5-2 are widely implemented to optimize match performance.[13]

Empirical studies by Forcher have indicated that the 4-4-2 and 4-2-3-1 formations are among the most frequently utilized strategies in professional football.[23] Additionally, research published in 2019[24] and 2023[25] demonstrated that the 4-2-3-1 formation significantly influences the physical and tactical performance of wingers in amateur football. Zhang *et al.*[26] further examined the impact of formations on the physical and technical performance of players in the Chinese Super League, concluding that formation selection has a direct effect on match outcomes. Case studies have also highlighted this impact; for example, in the 2009 UEFA Champions League Final, FC Barcelona secured a 2-0 victory over Manchester United by employing their signature 4-3-3 formation.[27] Furthermore, defensive formations, such as the 4-5-1 strategy, have been strategically implemented to reinforce defensive stability.[28]

Each football formation offers distinct strategic advantages, rendering them suitable for different styles of play. In this study, football formations were integrated into the artificial intelligence model's architecture in a unidirectional manner, consistent with the convolutional neural network framework. The dense block structure was adapted from DenseNet and the number of modified dense blocks in the hidden layers was determined based on the number of players in each position.[20] Specifically, defenders, midfielders, and forwards were assigned distinct layers, while the goalkeeper was designated as the input layer.

In the development of the football formation model, each group of players sequentially transitions into the next layer: the defense block transitions into the midfield block, which subsequently transitions into the Forward Block. Following feature extraction, the processed data is propagated to the fully connected layers, which incorporate batch normalization with ReLU activation and global average pooling to mitigate data redundancy before classification using the Softmax function.

The artificial intelligence models based on the four football formations were trained to distinguish between normal and cancerous breast ultrasound images. The performance of these models was influenced by hyperparameter configurations, including batch size and the number of training epochs. The results indicate that the 4-3-3 and 4-4-2 formations achieved optimal classification performance when trained with a batch size of 128 and 100 epochs. In contrast, the 4-2-3-1 and 5-4-1 formations yielded the best results with a batch size of 64 and 150 epochs.

These findings suggest that formations with a higher number of defense and midfield blocks necessitate a smaller batch size and an increased number of training iterations to attain optimal performance. Conversely, formations such as 4-3-3 and 4-4-2, which exhibit a balanced number of blocks, perform effectively with a larger batch size and fewer training iterations. Furthermore, the models exhibited similar prediction times across all formations, indicating that computational efficiency was maintained regardless of the selected formation.

Table 3 provides a comparative analysis of the breast cancer detection performance in this study relative to related research. The proposed model demonstrates superior performance compared to the study conducted by Rakibul Islam, which utilized the EDCNN method to classify breast ultrasound images into three categories: normal, benign, and malignant. Their study evaluated classification performance across three distinct image datasets, with the highest performance observed on the BUSI dataset, achieving an accuracy of 87.82%, a sensitivity of 85.33%, and a precision of 87.33%[21].

Table 3. Comparison of our proposed models and previous work.

Authors	Study	Model	Method	Test dataset (Images)	Training and validation dataset (Images)	Performance (%)
Islam[21]	Normal, benign, and malignant classification	EDCNN	Deep learning	BUSI Dataset 156	624	ACC 87.82 SEN 85.33 PRE 87.33
				UDAIT Dataset 33	130	ACC 85.69 SEN 78.00 PRE 84.00
				UDAIT Dataset 33	130	ACC 85.69 SEN 78.00 PRE 84.00
Umapathi[22]	Normal, benign, and malignant classification	SRAD	Deep learning	60	100	ACC 99.99 AUC 99.00 SEN 94.10 SPEC 96.12
Our proposed	Normal and breast cancer classification	OC-FFNet (4-4-2)	Deep learning	1,800	16,200	ACC 99.99 AUC 0.99 PRE 99.99 SEN 100.00 SPEC 99.99 F-1 99.99
		OC-FFNet (4-3-3)	Deep learning	1,800	16,200	ACC 99.99 AUC 0.99 PRE 99.99 SEN 100.00 SPEC 99.99 F-1 99.99
		OC-FFNet (5-4-1)	Deep learning	1,800	16,200	ACC 96.80 AUC 0.968 PRE 99.40 SEN 94.50 SPEC 99.40 F-1 96.90
		OC-FFNet (4-2-3-1)	Deep learning	1,800	16,200	ACC 96.30 AUC 0.963 PRE 92.70 SEN 100.00 SPEC 93.20 F-1 96.20

***Note**: ACC: accuracy, AUC: area under the curve, PRE: precision, SEN: sensitivity, SPEC: pecificity, F-1: F-1 score.*

Additionally, the performance of the proposed model is comparable to that of Umapathi's study, which employed the SRAD method for breast ultrasound image classification. Umapathi's model achieved an accuracy of 99.99%, a sensitivity of 99.00%, a specificity of 84.00%, and an area under the curve (AUC) of 99.00%.[22]

However, while both studies utilized artificial intelligence models to classify breast ultrasound images into three categories—normal, benign, and malignant, our study combined benign and malignant images into a single category.[16,29] Future research will focus on evaluating the proposed artificial intelligence model's effectiveness in a three-class classification setting. Nevertheless, this study utilized a larger dataset than both studies, which likely contributed to reducing the risk of overfitting during model training.

Furthermore, certain studies specifically assess the ability to differentiate between benign and malignant breast ultrasound images to evaluate classification performance.

Limitations

The dataset utilized in this study exhibited a high degree of similarity between images, presenting challenges in distinguishing between normal and cancerous cases. To mitigate this issue, image augmentation techniques were implemented to expand the dataset and enhance the model's ability to recognize subtle differences. Enhancing the diversity of both normal and cancerous ultrasound images would further improve the artificial intelligence model's learning process. A more varied dataset could contribute to better generalization and higher classification accuracy in real-world applications.

Using the proposed method, the augmented images may not clearly represent the target population. Future testing should include a greater number of images with similar characteristics or apply minimal augmentation to ensure better representation in the study.

Conclusion

The development of artificial intelligence model architectures based on football formations, incorporating modifications to the dense block structure in accordance with the number of players in each formation, yielded notable performance results. Among the four formations examined, the 4-4-2 and 4-3-3 models exhibited the highest efficiency, as their balanced distribution of modified dense blocks enhanced feature extraction capabilities. This structural advantage resulted in superior performance compared to the 4-2-3-1 and 5-4-1 formations. Nonetheless, all four models effectively distinguished between normal and cancerous breast ultrasound images when optimal parameter configurations were applied.

Conflict of interest

None

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Ethical Approval

This study was approved by the Ethics Committee of Naresuan University, Thailand (IRB No. P1-0114/2567).

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