A Systematic Literature Review of Convolutional Block Attention Module (CBAM) in Image Classification

Vincentius Bernando Wijaya[1*], Joko Siswantoro[2]

[1,2]Informatics Engineering, Faculty of Engineering, University of Surabaya, Surabaya, East Java, Indonesia
E-mail: [1*]s164224511@student.ubaya.ac.id, [2]joko_siswantoro@staff.ubaya.ac.id

(Received: 30 May 2026, revised: 25 Jun 2026, accepted: 26 Jun 2026)

Abstract

Image classification has become one of the most important tasks in computer vision and has been widely applied in medical imaging, agriculture, surveillance, and industrial systems. Recently, the Convolutional Block Attention Module (CBAM) has attracted significant attention for improving feature representation through channel and spatial attention mechanisms. However, studies on CBAM remain scattered across application domains, backbone architectures, deployment strategies, and evaluation approaches, making its implementation and effectiveness difficult to comprehensively understand. Therefore, this study conducted a Systematic Literature Review (SLR) based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to analyze CBAM implementation in image classification studies published between 2018 and 2025. The literature search used Google Scholar through the Publish or Perish application. Of 855 identified articles, 47 met the eligibility criteria and were included. The review analyzed research domains, backbone architectures, CBAM effectiveness, deployment positions, evaluation metrics, and cross-analytical relationships. Medical Imaging was the dominant application domain, while ResNet was the most frequently used backbone architecture. Analysis of 156 ablation experiments showed that 82.1% reported performance improvements after CBAM integration, whereas 91.5% of the reviewed studies demonstrated positive outcomes. Cross-analysis further indicated that CBAM was particularly effective for fine-grained visual recognition tasks, most commonly integrated within backbone architectures, and generally more compatible with residual-based than lightweight architectures. Furthermore, computational efficiency remained underreported. These findings provide a comprehensive synthesis of current CBAM research and practical guidance for future image classification studies.

Keywords: Convolutional Block Attention Module (CBAM), Image Classification, Attention Mechanism, Systematic Literature Review, PRISMA.

I. INTRODUCTION

Image classification is one of the fundamental problems in the field of computer vision [1]. The development of deep learning has significantly improved image classification performance through the ability of deep learning models to automatically learn hierarchical feature representations directly from raw data [2]. Deep learning-based image classification has been applied in several fields, including healthcare for medical image analysis, autonomous systems for object recognition, and security systems for face recognition and surveillance applications [1].

Despite these advancements, several challenges in image classification remain unresolved. The reliance on large labeled datasets and the high computational demands required for training deep learning models continue to be major limitations in model development [1], [2]. Furthermore, the complexity of deep learning algorithms and the dynamic nature of real-world problems make robust model development more challenging [3]. Other common challenges include limited training data, imbalanced datasets, and overfitting, which may reduce model accuracy and generalization capability [4].

To address these challenges, various attention mechanisms have been developed to improve feature representation quality in deep learning models. Attention mechanisms enable models to focus on relevant information while reducing the influence of less important patterns during feature extraction. One of the most widely used attention mechanisms in image classification is the Convolutional Block Attention Module (CBAM), introduced by Woo et al. [5]. CBAM combines channel attention and spatial attention to adaptively refine feature representations with relatively lightweight additional parameters and easy integration into various backbone architectures.

Over time, CBAM has been applied to various image classification domains and integrated with numerous deep

DOI: 10.34148/teknika.v15i2.1500

CC BY SA

learning backbones such as ResNet, EfficientNet, MobileNet, and custom Convolutional Neural Networks (CNNs). In the medical imaging domain, Zhang et al. integrated CBAM into the Attention Network for COVID-19 (ANC) to improve COVID-19 diagnosis performance using chest CT images [6]. In agriculture and plant science, Nigam et al. developed an EfficientNet-CBAM hybrid model for wheat rust severity classification by enhancing feature extraction through channel and spatial attention integration [7]. Furthermore, attention mechanisms have also been applied in fine-grained image classification through the combination of bilinear convolutional neural networks and attention mechanisms for Amanita species classification [8]. These studies show that CBAM has been applied across various domains and backbone architectures to improve feature representation and classification performance.

Several review studies have investigated the application of attention mechanisms in deep learning. Ghaffarian et al. conducted a systematic literature review on attention mechanism-based deep learning methods for remote sensing image processing [9]. Papanastasiou et al. reviewed attention-based architectures in medical image analysis [10], while Zacarias-Morales et al. presented a systematic review of attention mechanisms for medical diagnostic support systems [11]. Although these studies provide valuable insights into attention mechanisms, they mainly focus on specific domains such as remote sensing and medical image analysis and do not specifically examine CBAM implementation in image classification. To the best of our knowledge, no systematic literature review has comprehensively analyzed the application of CBAM in image classification across multiple domains. Meanwhile, the growing number of CBAM-based image classification studies has resulted in findings that are scattered across different application domains, backbone architectures, placement strategies, and evaluation approaches, making it difficult to obtain a comprehensive understanding of current research trends and effectiveness. Therefore, a systematic literature review is needed to synthesize existing evidence and provide a comprehensive overview of CBAM implementation in image classification.

This study conducts a systematic literature review to analyze CBAM implementation in image classification studies published between 2018 and 2025. The review focuses on identifying major research trends and implementation patterns of CBAM in image classification studies. Therefore, this study aims to answer the following research questions:

- **RQ1:** Which application domains most frequently implement CBAM in image classification tasks?
- **RQ2:** Which deep learning backbone architectures are most commonly combined with CBAM?
- **RQ3:** How effective is CBAM in improving model performance compared to baseline models without attention mechanisms?
- **RQ4:** Where is CBAM most commonly positioned within deep learning architectures?
- **RQ5:** How do CBAM-based studies evaluate model performance using classification metrics and computational metrics?

II. RESEARCH METHODOLOGY

This study employs a Systematic Literature Review (SLR) approach based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to systematically analyze the implementation of CBAM in image classification research [12]. The PRISMA framework was adopted to ensure that the literature identification, screening, eligibility assessment, and final selection processes were conducted systematically and transparently.

The literature search was performed using Google Scholar through the Publish or Perish application. The search strategy was designed to identify studies discussing CBAM implementation in deep learning-based image classification. The search query included keywords related to CBAM, image classification, deep learning architectures, evaluation metrics, and ablation studies. The complete search query is presented as follows: (intitle:"convolutional block attention module" OR intitle:"convolutional block attention-based" OR intitle:"CBAM" OR intitle:"attention mechanism") AND ("image classification") AND ("deep learning" OR "CNN" OR "convolutional neural network") AND ("accuracy" OR "F1-score" OR "recall" OR "precision") AND ("ablation study" OR "comparative study" OR "result comparison" OR "comparison study" OR "comparison of modeling").

The search focused on articles published between 2018 and 2025. All retrieved studies were managed using Zotero to assist in duplicate identification and reference organization. Based on the initial identification process, 855 articles were retrieved. After removing duplicates, 850 articles remained for the screening stage. The studies were then evaluated according to research relevance, CBAM implementation, article accessibility, and the availability of ablation studies. Following the eligibility assessment process, 47 final studies were selected for inclusion in this review.

The reduction from 855 initially identified articles to 47 final studies reflects the strict selection criteria applied in this review. The large number of initial results was intentionally generated through a broad search strategy to minimize the risk of missing relevant studies. However, most retrieved articles discussed attention mechanisms in general rather than evaluating CBAM through explicit ablation experiments. By excluding studies that did not meet the predefined eligibility criteria, the final set of 47 articles provides a focused and reliable representation of current CBAM research trends in image classification.

The inclusion and exclusion criteria were defined using the PICOT approach to ensure the selected studies aligned with the objectives of the research. The criteria used in this study are presented in Table 1.

Table 1. PICOT Criteria for Study Selection

PICOT	Inclusion Criteria	Exclusion Criteria
Population	Image datasets for image classification	Non-image datasets

PICOT	Inclusion Criteria	Exclusion Criteria
Intervention	Use of CBAM in deep learning architectures	Studies that do not use CBAM
Comparison	Includes comparison with baseline models without attention mechanisms	No baseline comparison
Outcome	Provides evaluation metrics such as accuracy, precision, recall, or F1-score	Does not report performance evaluation results
Time	Publications from 2018–2025	Publications outside the selected time range

Studies unrelated to image classification, studies without CBAM implementation or baseline comparison, inaccessible full-text articles, and studies lacking ablation experiments were excluded from the review process.

After the selection stage was completed, data from each study were systematically extracted to address the predefined research questions. The extracted information included application domain, backbone architecture, CBAM placement position, evaluation metrics, type of ablation experiment, and model performance improvement results. The extracted data were analyzed using descriptive and comparative approaches. The analysis results were presented using frequency distributions, percentages, bar charts, pie charts, and histograms. Figure 1 illustrates the study selection process used in this review.

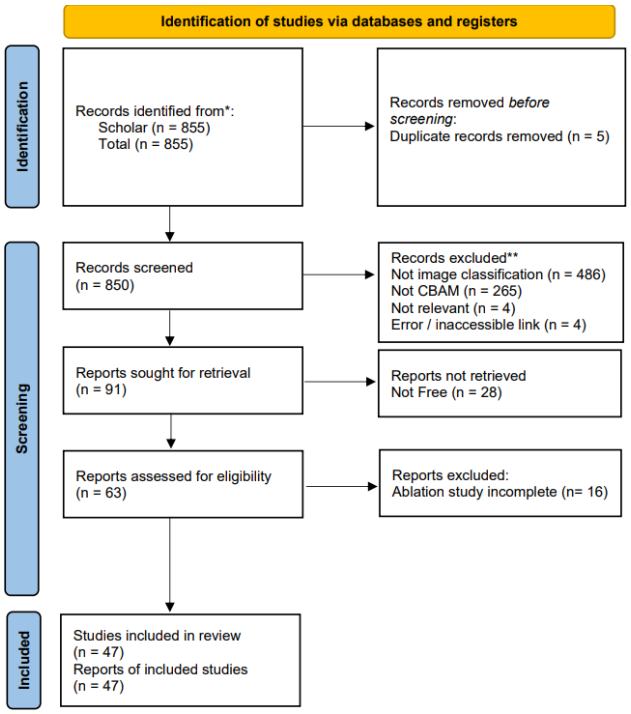


Figure 1. PRISMA Flow Diagram

ChatGPT (OpenAI) was utilized as a writing assistance tool during manuscript preparation. Its use was limited to language editing, grammar correction, and improving the clarity of academic writing. ChatGPT was not used to identify eligible studies, extract research data, perform statistical analyses, generate results, or formulate conclusions. All outputs generated by the AI tool were reviewed, verified, and approved by the authors before inclusion in the manuscript.

III. RESULTS AND DISCUSSION

This section presents the results of the systematic literature review based on the 47 selected studies. The analysis focuses on research domains, backbone architectures, CBAM placement strategies, evaluation metrics, and ablation experiments to address RQ1 to RQ5. Table 2 provides a summary of the selected studies.

Table 2. Selected Studies Included in the Systematic Review

Author	Domain	CBAM Position
Woo et al.[5]	General Computer Vision	Within/In the backbone
Zhang et al. [6]	Medical Imaging	Within/In the backbone
Nigam et al. [7]	Agriculture & Plant Science	Within/In the backbone
Wang et al. [8]	Food & Biological Classification	After backbone
Zeng et al. [13]	Remote Sensing & Earth Observation	After backbone
Nidhi and Verma [14]	Facial Expression & Emotion Recognition	Before backbone
Liu et al. [15]	Facial Expression & Emotion Recognition	Within/In the backbone
Fki et al. [16]	Medical Imaging	After backbone
Lan et al. [17]	Medical Imaging	Before backbone
Lv and Zhang [18]	Facial Expression & Emotion Recognition	Within/In the backbone
Liu et al. [19]	General Computer Vision	After backbone
He et al. [20]	Medical Imaging	After backbone
Xu et al. [21]	Environmental & Spectroscopy	Within/In the backbone
Zhou et al. [22]	Industrial & Predictive Maintenance	After backbone
Alhazmi and Altahhan [23]	Facial Expression & Emotion Recognition	Within/In the backbone
Oladimeji and Ibitoye [24]	Medical Imaging	After backbone
Wang et al. [25]	Agriculture & Plant Science	Within/In the backbone
Halim et al. [26]	Medical Imaging	Within/In the backbone

Author	Domain	CBAM Position
Wubineh et al. [27]	Medical Imaging	After backbone
Chen et al. [28]	Medical Imaging	After backbone
Chakraborty et al. [29]	Food & Biological Classification	After backbone
Rahman et al. [30]	Agriculture & Plant Science	After backbone
Wang et al. [31]	Remote Sensing & Earth Observation	Within/In the backbone
Pathmanaban [32]	Agriculture & Plant Science	After backbone
Nguyen et al. [33]	Transportation & Embedded AI	Within/In the backbone
Al Shafi et al. [34]	Medical Imaging	Within/In the backbone
Nigam et al. [35]	Agriculture & Plant Science	After backbone
Wang et al. [36]	Facial Expression & Emotion Recognition	Within/In the backbone
Amin et al. [37]	Surveillance & Security	Within/In the backbone
Potharaju et al. [38]	Medical Imaging	Within/In the backbone
Liao et al. [39]	Facial Expression & Emotion Recognition	Within/In the backbone
Zhu et al. [40]	Agriculture & Plant Science	After backbone
Wahyunigrum et al. [41]	Agriculture & Plant Science	Within/In the backbone
Lin et al. [42]	Surveillance & Security	Within/In the backbone
Alirezazadeh et al. [43]	Agriculture & Plant Science	After backbone
Wu et al. [44]	Medical Imaging	After backbone
Guo et al. [45]	Agriculture & Plant Science	Within/In the backbone
Zhong et al. [46]	General Computer Vision	After backbone
Ijaz et al. [47]	Medical Imaging	Within/In the backbone
Fauzi and Suciati [48]	Food & Biological Classification	Within/In the backbone
Nasra et al. [49]	Agriculture & Plant Science	After backbone
Liao et al. [50]	Facial Expression & Emotion Recognition	Within/In the backbone
Liu and Tian [51]	General Computer Vision	Within/In the backbone
Wu et al. [52]	OCR & Character Recognition	Within/In the backbone
Peng et al. [53]	Agriculture & Plant Science	Within/In the backbone
Li et al. [54]	Industrial & Predictive Maintenance	Within/In the backbone
Bandaru et al. [55]	Medical Imaging	Within/In the backbone

A. Research Domain Distribution

The analysis of RQ1 shows that CBAM is most commonly applied in the Medical Imaging domain, followed by Agriculture & Plant Science and Facial Expression & Emotion Recognition. Figure 2 illustrates the distribution of application domains identified in the selected studies.

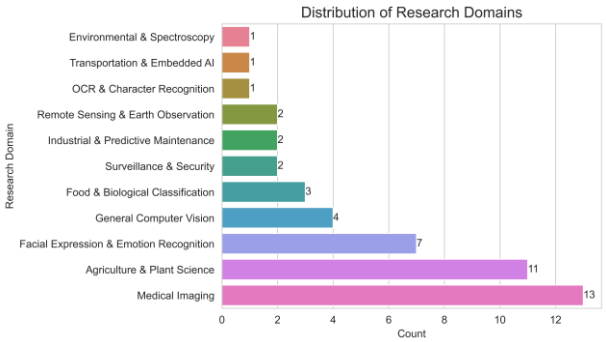


Figure 2. Distribution of Research Domains

In addition, several studies were identified in the domains of General Computer Vision, Food & Biological Classification, Surveillance & Security, Industrial & Predictive Maintenance, OCR & Character Recognition, Transportation & Embedded AI, and Remote Sensing & Earth Observation.

The dominance of the Medical Imaging domain indicates that CBAM is widely applied in image classification tasks requiring detailed feature extraction and complex spatial representation capabilities.

B. Backbone Architecture Distribution

The results of RQ2 show that the most commonly used backbone family integrated with CBAM is ResNet, with a total of 20 studies. EfficientNet, MobileNet, and Custom CNN architectures were each used in 8 studies. Figure 3 presents the distribution of backbone architectures integrated with CBAM across the selected studies.

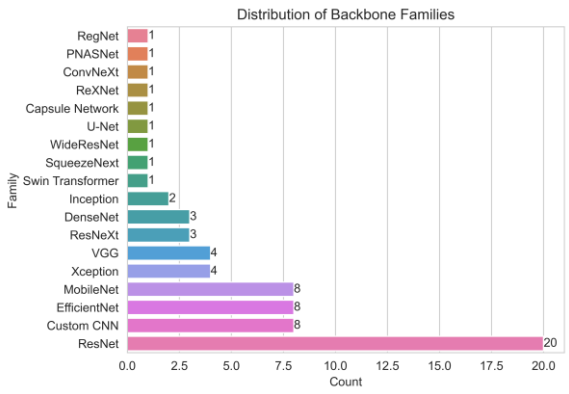


Figure 3. Distribution of Backbone Families

DOI: 10.34148/teknika.v15i2.1500
CC BY SA

Other backbone architectures identified in the selected studies include Xception, VGG, ResNeXt, DenseNet, Inception, Swin Transformer, Capsule Network, ConvNeXt, RegNet, and several other architectures with lower usage frequencies.

These findings indicate that CBAM is most frequently integrated into residual learning-based backbones, particularly ResNet.

C. Effectiveness of CBAM Integration

The results of RQ3 indicate that, based on the analysis of the 47 selected studies, a total of 156 ablation experiments were identified to evaluate the effectiveness of CBAM integration across various backbone architectures and image classification domains. Most studies conducted only a small number of ablation experiments, typically between 1 and 4 experiments. Among all selected studies, 38 studies conducted fewer than five ablation experiments, while only a small number of studies performed more extensive architectural explorations with larger numbers of experiments. The distribution of ablation experiments conducted across the selected studies is shown in Figure 4.

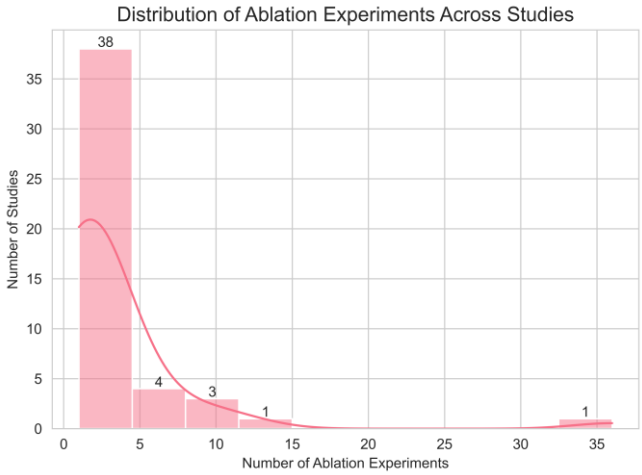


Figure 4. Distribution of Ablation Experiments Across Studies

The analysis results also indicate that the majority of experiments adopted a pure CBAM ablation approach. Out of the 156 identified experiments, 138 experiments (88.5%) used direct comparisons between baseline models and baseline models integrated with CBAM without any additional architectural modifications. Meanwhile, 18 experiments (11.5%) used hybrid ablation approaches. In these experiments, CBAM was combined with additional components such as feature fusion modules, other attention mechanisms, or backbone architecture modifications. Figure 5 illustrates the proportion of pure CBAM ablation and hybrid ablation experiments identified in this review.

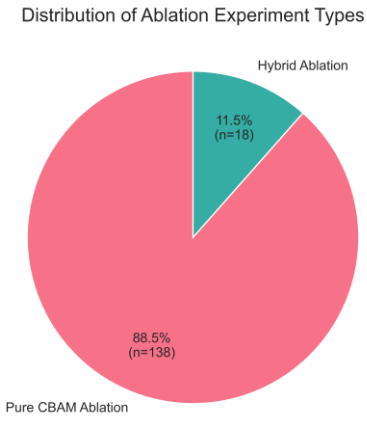


Figure 5. Distribution of Ablation Experiment Types

In addition to experiment type analysis, this study also evaluated the distribution of model performance improvements after CBAM integration. Based on the extracted experimental results, 82.1% of the experiments demonstrated performance improvements compared to baseline models without attention mechanisms, while 17.9% of the experiments did not show significant improvements. The distribution of performance improvement results after CBAM integration is presented in Figure 6.

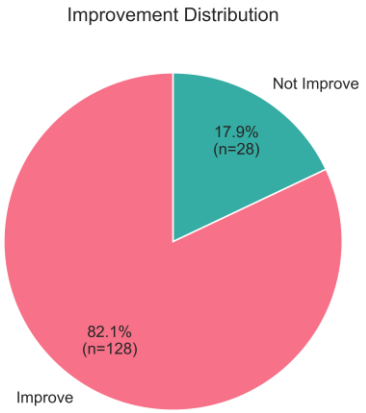


Figure 6. Improvement Distribution

Although the experiment-level analysis provides useful insights into individual ablation settings, multiple experiments originating from the same study cannot be considered statistically independent because they share similar datasets, architectures, and experimental conditions. Therefore, an additional study-level analysis was conducted by treating each paper as a single unit of analysis. A study was categorized as showing improvement when the majority of its reported ablation experiments demonstrated better performance after CBAM integration compared with the corresponding baseline models. Based on this criterion, 43 out of 47 studies (91.5%) were classified as improved, while only 4 studies (8.5%) were classified as not improved. The distribution of performance improvements at the study level is presented in Figure 7.

DOI: 10.34148/teknika.v15i2.1500
CC BY SA

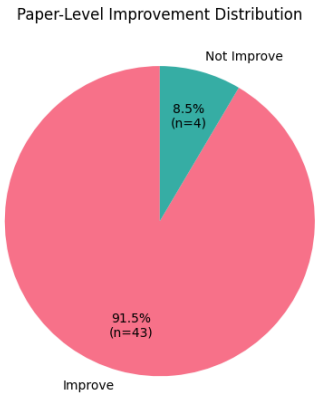


Figure 7. Paper-Level Improvement Distribution

The high proportion of studies reporting performance improvements suggests that CBAM provides practical benefits across a wide range of image classification applications. A common observation among the reviewed studies is that CBAM was particularly useful in tasks requiring the identification of subtle visual characteristics, such as medical abnormalities, plant diseases, and facial expressions. For example, Zhang et al. [6] reported that CBAM helped the model focus on lesion-related regions in chest CT images for COVID-19 diagnosis, while Nigam et al. [7] showed that CBAM improved the recognition of disease severity patterns in wheat leaves. Similar findings were also reported by Wang et al. [25] and Peng et al. [53] in agricultural image classification tasks. These studies consistently indicate that CBAM contributes by emphasizing task-relevant image regions while reducing the influence of irrelevant background information.

However, the findings also suggest that CBAM is not universally beneficial. Several studies reported limited or inconsistent improvements, indicating that the effectiveness of CBAM depends on factors such as dataset characteristics, feature complexity, and backbone architecture. Therefore, CBAM should be viewed as a generally effective enhancement mechanism rather than a guaranteed solution for all image classification problems.

D. CBAM Placement Strategy

The results of RQ4 show that the most common CBAM placement strategy was inside the backbone architecture, identified in 27 studies. Meanwhile, 18 studies placed CBAM after the backbone, while only 2 studies positioned CBAM before the backbone. Figure 8 illustrates the distribution of CBAM placement strategies within deep learning architectures.

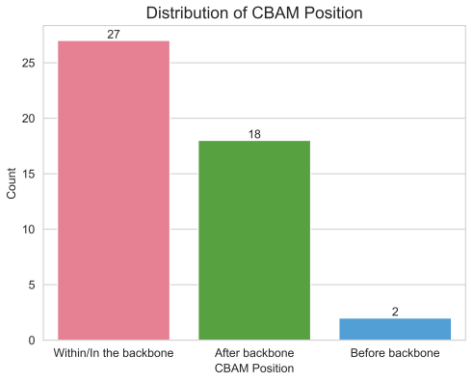


Figure 8. Distribution of CBAM Position

Based on the distribution proportions, 57.4% of the studies placed CBAM inside the backbone, 38.3% after the backbone, and 4.3% before the backbone. The proportion of CBAM placement positions identified in the selected studies is presented in Figure 9.

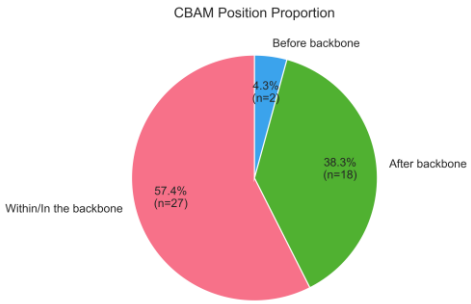


Figure 9. CBAM Position Proportion

These findings indicate that integrating CBAM within the backbone architecture is the most widely adopted deployment strategy in image classification studies. This preference was consistently observed across domains such as medical imaging, agriculture, and facial expression recognition. Studies such as Zhang et al. [6], Wang et al. [25], and Peng et al. [53] integrated CBAM directly into backbone layers and reported improved classification performance. The widespread adoption of this strategy suggests that researchers consider feature refinement during the feature extraction process to be a practical approach for enhancing feature representation while preserving the overall backbone architecture. However, its popularity does not necessarily imply superior effectiveness compared with alternative placement strategies, which are further examined in the cross-analytical meta-synthesis section.

E. Evaluation Metrics Analysis

The results of RQ5 indicate that accuracy was the most frequently used evaluation metric and was identified in all selected studies. In addition, recall and F1-score were each reported in 32 studies, while precision was reported in 31 studies. Figure 10 presents the frequency of evaluation metrics used in CBAM-based image classification studies.

DOI: 10.34148/teknika.v15i2.1500

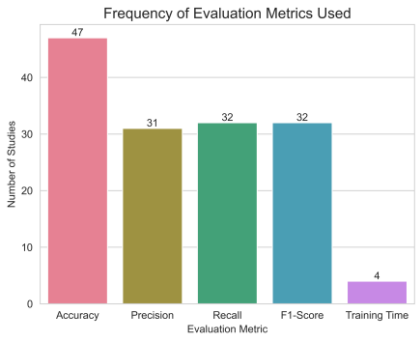


Figure 10. Frequency of Evaluation Metrics Used

On the other hand, only a small number of studies reported computational metrics such as training time. This finding indicates that most studies still focus primarily on improving classification performance rather than model computational efficiency.

F. Cross-Analytical Meta-Synthesis

To move beyond descriptive frequency analysis, this section performs a cross-analytical meta-synthesis by relating performance outcomes to research domains, CBAM deployment positions, and backbone architecture families. The objective is to identify the conditions under which CBAM tends to provide the greatest performance benefits and the situations where its effectiveness appears to be more limited.

Table 3 presents the relationship between research domains and CBAM performance outcomes at the study level. The results show that CBAM consistently performs well in domains that require detailed visual feature extraction, such as Medical Imaging (92.31%), Agriculture & Plant Science (90.91%), and several domains that achieved a 100% success rate, including Facial Expression Recognition, OCR, Remote Sensing, and Surveillance. These findings suggest that CBAM is particularly beneficial for tasks involving localized patterns and fine-grained visual features.

In contrast, lower success rates were observed in Industrial & Predictive Maintenance (50%) and Environmental & Spectroscopy (0%). A possible explanation is that these domains often rely on structured sensor or spectral representations rather than natural image features, reducing the benefits provided by spatial attention mechanisms.

Table 3. Cross-Analysis of Research Domains and CBAM Performance Outcomes

Domains	Improve		
	Yes	No	Success Rate
Agriculture & Plant Science	10	1	90.91%
Environmental & Spectroscopy	0	1	0.00%
Facial Expression & Emotion Recognition	7	0	100.00%
Food & Biological Classification	3	0	100.00%
General Computer Vision	4	0	100.00%
Industrial & Predictive Maintenance	1	1	50.00%
Medical Imaging	12	1	92.31%
OCR & Character Recognition	1	0	100.00%
Remote Sensing & Earth Observation	2	0	100.00%
Surveillance & Security	2	0	100.00%
Transportation & Embedded AI	1	0	100.00%

Table 4 presents the relationship between CBAM placement and performance outcomes. Although most studies integrated CBAM within the backbone architecture, placing CBAM after the backbone achieved a higher success rate (94.44%) compared with integration within the backbone (88.89%). Meanwhile, the two studies that placed CBAM before the backbone both reported positive results.

These findings suggest that applying CBAM after the backbone may be a more robust strategy because attention is applied to high-level feature representations without modifying intermediate feature extraction processes. However, all placement strategies generally showed high success rates, indicating that CBAM remains effective across different deployment configurations.

Table 4. Cross-Analysis of CBAM Positions and Performance Outcomes

Position	Improve		
	Yes	No	Success Rate
After backbone	17	1	94.44%
Before backbone	2	0	100.00%
Within/In the backbone	24	3	88.89%

Table 5 presents the relationship between backbone families and CBAM performance outcomes at the experiment level. CBAM showed strong compatibility with most architectures, including ResNet (85.71%), EfficientNet (90.91%), VGG (91.67%), and Custom CNNs (92.31%). Several architectures, such as SqueezeNext, U-Net, Swin Transformer, and RegNet, achieved a 100% success rate.

However, lower success rates were observed in MobileNet (62.07%), Xception (66.67%), Inception (66.67%), and ResNeXt (66.67%). This may indicate that architectures with highly optimized feature extraction mechanisms gain less consistent benefits from CBAM. Overall, the findings suggest that CBAM effectiveness depends not only on the attention mechanism itself but also on the characteristics of the backbone architecture.

Table 5. Cross-Analysis of Backbone Families and Performance Outcomes

Backbone	Improve		
	Yes	No	Success Rate
ResNet	48	8	85.71%
MobileNet	18	11	62.07%
Custom CNN	12	1	92.31%
VGG	11	1	91.67%
EfficientNet	10	1	90.91%

DOI: 10.34148/teknika.v15i2.1500
CC BY SA

DenseNet	5	1	83.33%
Xception	4	2	66.67%
SqueezeNext	5	0	100.00%
Inception	2	1	66.67%
ResNeXt	2	1	66.67%
U-Net	3	0	100.00%
Swin Transformer	2	0	100.00%
WideResNet	2	0	100.00%
Capsule Network	1	0	100.00%
ConvNeXt	0	1	0.00%
PNASNet	1	0	100.00%
RegNet	1	0	100.00%
ReXNet	1	0	100.00%

G. Limitations of the Study

This review has several limitations. The literature search was conducted exclusively through Google Scholar using the Publish or Perish application. Although Google Scholar provides broad coverage of scholarly publications, relevant studies indexed in databases such as IEEE Xplore, Scopus, or ACM Digital Library may not have been captured. Therefore, the findings and trends identified in this review should be interpreted within the scope of the selected database and eligibility criteria. Future studies may improve the comprehensiveness of the review by incorporating multiple academic databases and conducting cross-database validation.

IV. CONCLUSION

This systematic literature review analyzed 47 studies on the implementation of Convolutional Block Attention Module (CBAM) in image classification research published between 2018 and 2025. The findings indicate that CBAM has been widely adopted across various application domains and backbone architectures, with Medical Imaging emerging as the most dominant research domain and ResNet as the most frequently used backbone architecture. Most studies reported improved classification performance after CBAM integration, confirming its practical value as an attention mechanism for enhancing feature representation.

The cross-analytical meta-synthesis further revealed that the effectiveness of CBAM is influenced by both application domain and architectural design. CBAM achieved particularly high success rates in Medical Imaging and Agriculture & Plant Science, suggesting that the module is especially beneficial for tasks involving fine-grained visual patterns and localized features. In contrast, lower success rates were observed in domains such as Environmental & Spectroscopy and Industrial & Predictive Maintenance, indicating that the benefits of CBAM may depend on the characteristics of the underlying data.

In terms of deployment strategy, although CBAM was most commonly integrated within backbone architectures, studies placing CBAM after the backbone achieved slightly higher success rates. Furthermore, CBAM demonstrated strong compatibility with most backbone families but showed less consistent benefits in several lightweight architectures, particularly MobileNet and Xception. Finally, this review found that existing studies predominantly focus on classification performance metrics, while computational efficiency remains underreported. Future research should therefore investigate both performance and efficiency aspects to better understand the practical trade-offs of CBAM deployment in real-world applications.

REFERENCES

[1] S. Gorai, A. Sarangi, and S. Pradhan, "Deep Learning for Image Classification: Methods, Challenges, and Future Directions," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 11, pp. 484–496, 2025, doi: 10.32628/CSEIT2511110.

[2] M. Trigka and E. Dritsas, "A comprehensive survey of deep learning approaches in image processing," *Sensors*, vol. 25, no. 2, p. 531, 2025.

[3] M. H. M. Noor and A. O. Ige, "A survey on state-of-the-art deep learning applications and challenges," *Eng. Appl. Artif. Intell.*, vol. 159, p. 111225, 2025.

[4] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J. Big Data*, vol. 8, no. 1, p. 53, 2021.

[5] S. Woo, J. Park, J. Y. Lee, and ..., "Cbam: Convolutional block attention module," *Proceedings of the ...*, 2018, [Online]. Available: http://openaccess.thecvf.com/content_ECCV_2018/html/Sanghyun_Woo_Convolutional_Block_Attention_ECCV_2018_paper.html

[6] Y. Zhang, X. Zhang, and W. Zhu, "ANC: Attention network for COVID-19 explainable diagnosis based on convolutional block attention module," *Computer Modeling in Engineering ...*, 2021, [Online]. Available: https://www.ingentaconnect.com/contentone/tsp/cmes/2021/00000127/00000003/art00010

[7] S. Nigam, R. Jain, V. K. Singh, A. K. Singh, and ..., "Automated severity level estimation of wheat rust using an EfficientNet-CBAM hybrid model," *Frontiers in Plant ...*, 2025, doi: 10.3389/fpls.2025.1540642.

[8] P. Wang *et al.*, "Classification of Amanita Species Based on Bilinear Networks with Attention Mechanism," *Agriculture*, 2021, [Online]. Available: https://www.mdpi.com/2077-0472/11/5/393

[9] S. Ghaffarian, J. Valente, M. Van Der Voort, and B. Tekinerdogan, "Effect of attention mechanism in deep learning-based remote sensing image processing: A systematic literature review," *Remote Sens. (Basel).*, vol. 13, no. 15, p. 2965, 2021.

[10] G. Papanastasiou, N. Dikaios, J. Huang, C. Wang, and G. Yang, "Is attention all you need in medical image analysis? A review," *IEEE J. Biomed. Health Inform.*, vol. 28, no. 3, pp. 1398–1411, 2023.

[11] N. Zacarias-Morales, P. Pancardo, J. A. Hernández-Nolasco, and M. Garcia-Constantino, "Artificial Neural Network, Attention Mechanism and Fuzzy Logic-Based Approaches for Medical Diagnostic Support: A Systematic Review," *AI*, vol. 6, no. 11, p. 281, 2025.

[12] M. J. Page *et al.*, "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *bmj*, vol. 372, 2021.

[13] H. Zeng, S. Zou, C. Yao, and C. Xu, "… Symmetric Dual-Branch Lightweight Model for Remote Sensing Scene Classification Based on Lie Group Feature Extraction and Cross-Attention Mechanism," *Symmetry (Basel).*, 2025, [Online]. Available: https://www.mdpi.com/2073-8994/17/5/780

[14] Nidhi and B. Verma, "A lightweight convolutional swin transformer with cutmix augmentation and CBAM attention for compound emotion recognition: Nidhi and V. Bindu," *Applied Intelligence*, 2024, doi: 10.1007/s10489-024-05598-5.

[15] J. Liu, X. Lin, R. Li, Y. Han, and J. Chen, "A Lightweight Method Based on Wavelet Channel Attention Mechanism and Knowledge Distillation for Facial Expression Recognition," *Available at SSRN 5142684*, [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5142684

[16] Z. Fki, B. Ammar, R. Fourati, H. Fendri, A. Hussain, and ..., "A novel IoT-based deep neural network for COVID-19 detection using a soft-attention mechanism," *Multimedia Tools and …*, 2024, doi: 10.1007/s11042-023-17642-6.

[17] Z. Lan, S. Cai, J. Zhu, and Y. Xu, *A novel skin cancer assisted diagnosis method based on capsule networks with CBAM*. techrxiv.org, 2025. doi: 10.36227/techrxiv.23291003.

[18] C. Lv and K. Zhang, "A Research of Improved Facial Expression Recognition Method Based on CBAM and Joint-normalization Techniques," *Proceedings of the 8th International Conference on …*, 2023, doi: 10.1145/3617184.3617188.

[19] X. Liu, W. Luo, J. Du, X. Wang, Y. Dang, and Y. Liu, "A robust generalized zero-shot learning method with attribute prototype and discriminative attention mechanism," *Electronics (Basel).*, 2024, [Online]. Available: https://www.mdpi.com/2079-9292/13/18/3751

[20] C. He, J. Zhang, Y. Liang, and H. Li, "A unified framework harnessing multi-scale feature ensemble and attention mechanism for gastric polyp and protrusion identification in gastroscope imaging," *Sci. Rep.*, 2025, [Online]. Available: https://www.nature.com/articles/s41598-025-90034-y

[21] R. Z. Xu *et al.*, "Attention improvement for data-driven analyzing fluorescence excitation-emission matrix spectra via interpretable attention mechanism," *NPJ Clean Water*, 2024, [Online]. Available: https://www.nature.com/articles/s41545-024-00367-w

[22] Y. Zhou, J. Wang, and Z. Wang, "Bearing faulty prognostic approach based on multiscale feature extraction and attention learning mechanism," *J. Sens.*, 2021, doi: 10.1155/2021/6221545.

[23] M. Alhazmi and A. Altahhan, "Best fit activation functions for attention mechanism: Comparison and enhancement," *2023 International Joint Conference …*, 2023, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10191885/

[24] O. O. Oladimeji and A. O. J. Ibitoye, "Brain tumor classification using ResNet50-convolutional block attention module," *Applied Computing and Informatics*, 2023, doi: 10.1108/ACI-09-2023-0022/1248435.

[25] J. Wang *et al.*, "CBAM-ResNet34-based classification and evaluation method for developmental processes of greenhouse strawberries," *bioRxiv*, 2024, doi: 10.1101/2024.12.03.626693.abstract.

[26] C. Halim, N. G. E. Putra, N. A. Nugroho, and ..., "Chest X-ray Image Classification to Identify Lung Diseases Using Convolutional Neural Network and Convolutional Block Attention Module," *JOIV: International Journal …*, 2023, [Online]. Available: https://www.joiv.org/index.php/joiv/article/view/1136

[27] B. Z. Wubineh, A. Rusiecki, K. Halawa, and ..., "Classification of Brain Tumor Using MobileNet and CBAM-Based Deep Learning Approach from MRI Images," *… on Information and …*, 2025, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/11282698/

[28] C. Chen *et al.*, "Classification of multi-differentiated liver cancer pathological images based on deep learning attention mechanism," *BMC Medical Informatics …*, 2022, doi: 10.1186/s12911-022-01919-1.

[29] B. Chakraborty, R. Mukherjee, and S. Mandal, "Convolutional block attention-based deep neural network for mushroom classification," *Discover Artificial Intelligence*, 2025, doi: 10.1007/s44163-025-00488-2.

[30] M. A. Rahman, M. Ullah, R. K. Devnath, and ..., "Cotton leaf disease detection: an integration of CBAM with deep learning approaches," *Int J Comput …*, 2025, [Online]. Available: https://www.researchgate.net/profile/Rimon-Devnath/publication/389319663_Cotton_Leaf_Disease_Detection_An_Integration_of_CBAM_with_Deep_Learning_Approaches/links/67be0ea8461fb56424e9ca15/Cotton-Leaf-Disease-Detection-An-Integration-of-CBAM-with-Deep-Learning-Approaches.pdf

[31] X. Wang, L. Yuan, H. Xu, and X. Wen, "CSDS: End-to-end aerial scenes classification with depthwise separable convolution and an attention mechanism," *IEEE Journal of Selected …*, 2021, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9560010/

[32] P. Pathmanaban, "Digitized Visual Measurement System Using MobileNetV2–CBAM for Automated Sapota Quality Grading," *Available at SSRN 5784252*,

[Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5784252
[33] D. L. Nguyen, M. D. Putro, and K. H. Jo, "Driver behaviors recognizer based on light-weight convolutional neural network architecture and attention mechanism," *IEEE Access*, 2022, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9810252/
[34] A. Al Shafi, S. R. Suma, and ..., "DSCBAM-Net: A Lightweight Neural Network with Grouped Depthwise-Separable CBAM for Automated Brain Tumor Classification," *2025 7th International …*, 2025, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/11355571/
[35] S. Nigam, R. Jain, V. K. Singh, S. Marwaha, A. Arora, and ..., "EfficientNet architecture and attention mechanism-based wheat disease identification model," *Procedia Computer …*, 2024, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050924007142
[36] S. Wang, S. Liu, M. Jin, and M. Yuan, "Emotion recognition in Dunhuang Mogao mural figures via PNASNet-CBAM," *npj Heritage Science*, 2025, [Online]. Available: https://www.nature.com/articles/s40494-025-01961-y
[37] S. U. Amin, M. S. Abbas, B. Kim, Y. Jung, and S. Seo, "Enhanced anomaly detection in pandemic surveillance videos: an attention approach with EfficientNet-B0 and CBAM integration," *IEEE Access*, 2024, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10740272/
[38] S. Potharaju, S. N. Tambe, K. Dasari, N. Srikanth, and ..., "Enhanced X-ray image Classification for Pneumonia Detection Using Deep Learning Based CBAM and SE Mechanisms," *Intelligence-Based …*, 2025, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666521225001036
[39] J. Liao, Y. Lin, T. Ma, S. He, X. Liu, and G. He, "Facial expression recognition methods in the wild based on fusion feature of attention mechanism and LBP," *Sensors*, 2023, [Online]. Available: https://www.mdpi.com/1424-8220/23/9/4204
[40] X. Zhu, X. Zhang, Z. Sun, Y. Zheng, S. Su, and F. Chen, "Identification of Oil Tea (Camellia oleifera C.Abel) Cultivars Using EfficientNet-B4 CNN Model with Attention Mechanism," *Forests*, 2021, [Online]. Available: https://www.mdpi.com/1999-4907/13/1/1
[41] R. T. Wahyunigrum, I. A. Siradjuddin, T. D. Farawati, and ..., "Implementation of an EfficientNet-B4 Model Architecture with a Convolutional Block Attention Module (CBAM) for Betel Leaf Disease Classification," *… , Technology &Applied …*, 2025, [Online]. Available: https://www.etasr.com/index.php/ETASR/article/view/11900
[42] H. Lin, W. Luo, K. Wei, and M. Liu, "Improved xception with dual attention mechanism and feature fusion for face forgery detection," *2022 4th International Conference …*, 2022, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9984903/
[43] P. Alirezazadeh, M. Schirrmann, and F. Stolzenburg, "Improving deep learning-based plant disease classification with attention mechanism," *Gesunde Pflanzen*, 2023, doi: 10.1007/s10343-022-00796-y.
[44] M. N. Wu, K. He, Y. B. Yu, B. Zheng, S. J. Zhu, and ..., "Intelligent diagnostic model for pterygium by combining attention mechanism and MobileNetV2," *International …*, 2024, [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11246929/
[45] Y. Guo, M. Ma, and Z. Wang, "Leaf Classification for Local Area Network Deployment: Comparison and Pruning of Resnet18 and Attention Modules (SE/CBAM)," *Highlights in Science, Engineering and …*, 2025, [Online]. Available: http://datahset.com/index.php/ojs/article/view/19
[46] S. Zhong, W. Wen, and J. Qin, "Mix-pooling strategy for attention mechanism," *arXiv preprint arXiv:2208.10322*, 2022, [Online]. Available: https://arxiv.org/abs/2208.10322
[47] A. Ijaz, B. Raza, I. Kiran, A. Waheed, A. Raza, and ..., "Modality specific CBAM-VGGNet model for the classification of breast histopathology images via transfer learning," *IEEE …*, 2023, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10044107/
[48] M. Z. Fauzi and N. Suciati, "Modified CBAM-VGG16 with Sequential SAM-CAM and Image Filtering for Automated Microscopic Fungi Classification.," *… Journal of Robotics &Control Systems*, 2025, [Online]. Available: https://search.ebscohost.com/login.aspx?direct=true\&profile=ehost\&scope=site\&authtype=crawler\&jrnl=27752658\&AN=191252233\&h=DzMqloRgozlXjMI%2Foq27O5cgJvZCPF9ejI2M6qilqbIpTpM3%2B%2BMu40HRMtPLNeFRh0sDgaG%2BhwYpW7%2BscR9%2B8A%3D%3D\&crl=c
[49] P. Nasra, J. Singh, S. Rani, G. Shandilya, S. Bharany, and ..., "Optimized ReXNet variants with spatial pyramid pooling, CoordAttention, and convolutional block attention module for money plant disease detection," *Discover …*, 2025, doi: 10.1007/s43621-025-01241-6.
[50] L. Liao, S. Wu, C. Song, and J. Fu, "PH-CBAM: A parallel hybrid CBAM network with multi-feature extraction for facial expression recognition," *Electronics (Basel).*, 2024, [Online]. Available: https://www.mdpi.com/2079-9292/13/16/3149
[51] Y. Liu and J. Tian, "Probabilistic attention map: a probabilistic attention mechanism for convolutional neural networks," *Sensors*, 2024, [Online]. Available: https://www.mdpi.com/1424-8220/24/24/8187
[52] R. Wu, F. Zhou, N. Li, X. Liu, and R. Wang, "Reconstructed SqueezeNext with C-CBAM for offline

handwritten Chinese character recognition," *PeerJ Comput. Sci.*, 2023, [Online]. Available: https://peerj.com/articles/cs-1529/

[53] J. Peng, Y. Wang, P. Jiang, R. Zhang, and H. Chen, "RiceDRA-net: precise identification of rice leaf diseases with complex backgrounds using a res-attention mechanism," *Applied Sciences*, 2023, [Online]. Available: https://www.mdpi.com/2076-3417/13/8/4928

[54] Y. Li, G. Cui, Q. Han, S. Chen, and S. Lu, "Risk assessment model for dust explosion in dust removal pipelines using an attention mechanism-based convolutional neural network," *Stochastic Environmental Research …*, 2024, doi: 10.1007/s00477-024-02781-5.

[55] S. C. Bandaru, G. B. Mohan, R. P. Kumar, and ..., "SwinGALE: fusion of swin transformer and attention mechanism for GAN-augmented liver tumor classification with enhanced deep learning," *International Journal of …*, 2024, doi: 10.1007/s41870-024-02168-3.