International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

ArtiScan: A Model for Identification and Time Period Prediction for Artifacts

Ms. Suman Arora[1], Dhruv Chandhok[2], Pranshu Kaushik[3], Rupashi Goel[4], Soven Dara[5]

[1]Assistant Professor, Deptt. of Computer Science & Engineering Bhagwan Parshuram Institute of Technology Delhi, India
[1]suman@bpitindia.edu.in,
[2]B. Tech Scholar, Deptt. of Computer Science & Engineering Bhagwan Parshuram Institute of Technology Delhi, India
[2]dkc6802@gmail.com, [3]pranshukaushik1@gmail.com, [4]rupashigoel8@gmail.com, [5]sovendara19@gmail.com

ABSTRACT-

The classification and dating of artifacts have traditionally relied on manual methods, posing challenges in terms of time, subjectivity, and human error. This research proposes an innovative approach by leveraging deep learning techniques, specifically Convolutional Neural Networks (CNNs), to automate and enhance artifact analysis. The primary objectives are accurate artifact identification and time-period prediction for coin artifacts.

Two distinct CNN models are developed: Model 1 for artifact classification, distinguishing coins from other artifacts, and Model 2 for time-period prediction of coin artifacts. Trained on a diverse dataset of artifact images spanning various historical periods, Model 1 achieves an impressive 95% accuracy in differentiating coins from other artifacts. Building upon this, Model 2 accurately classifies coin artifacts into broad historical eras, such as Roman, Medieval, and Post-Medieval, with 59.6% accuracy.

A user-friendly interface, developed using Python's Tkinter library, enables seamless artifact image upload and analysis. Users, including archaeologists, museum curators, and enthusiasts, receive classification results and, for coins, predicted time periods.

By combining deep learning, carefully designed CNN architectures, and an accessible interface, this research presents an automated solution for artifact analysis. The proposed approach holds significant potential for applications in archaeological research, museum curation, and public engagement, ultimately contributing to a deeper understanding of cultural heritage.

1.Introduction

Artifacts have been vital windows into the past since the beginning of human civilization, providing tangibly real views into the lives, civilizations, and technological innovations of our ancestors. These artifacts from ancient times, which range from complex coins and pottery to intricate sculptures and simple tools, have fascinated archaeologists, numismatists, and historians and have driven them to continue their unwavering quest to piece together the complex history of humanity.

Artifact analysis, the study of artifacts, has been crucial in reassembling the stories of past civilizations, following the complex webs of commerce and cultural interchange, and illuminating the social development that has molded our planet. But historically, this has been a labor-intensive and frequently subjective procedure that has mostly relied on the skilled eyes and knowledge of experts to spot distinctive characteristics, patterns, and symbolic representations that allude to the history, function, and provenance of an object.

1.1. Background and Challenges in Artifact Analysis

Historically, the process of classifying artifacts has been laborious and manual, requiring a high level of domain expertise as well as careful attention to detail. The minute details of every artifact, such as the elaborate designs etched on ancient coins or the minute variances in pottery types and sculpting processes, have been examined by archaeologists and numismatists for numerous hours. Despite its great value, this procedure is prone to biases resulting from subjective interpretations, human error, and inconsistency.

Moreover, even the most experienced experts may become overwhelmed by the sheer amount of items uncovered.

during archaeological excavations, which can cause bottlenecks and delays in the study process. The backlog of unidentified artifacts increases as new discoveries are made, impeding research efforts, and narrowing our comprehension of the rich tapestry of human legacy.

1.2. The Potential of Deep Learning in Artifact Analysis

Recent advances in deep learning, and in particular the use of Convolutional Neural Networks (CNNs), have revolutionized computer vision and image processing. Inspired by the complex processes of the human visual cortex, CNNs have shown an exceptional ability to extract complex visual properties from picture data, which allows them to perform tasks like object recognition, classification, and pattern detection with surprising proficiency. Deep learning techniques have made it possible to automate and improve the artifact analysis process in ways never before possible. This has paved the way for classification procedures that are more effective, reliable, and objective. By utilizing CNNs, researchers can make use of these models' capacity to acquire complex patterns and visual aids, thereby simulating and enhancing the skills of human analysts.

1.3. Objectives and Significance of the Research

Inspired by deep learning's transformative potential and the urgent need for expedited artifact analysis, this research aims to create a holistic solution that tackles two main goals:

1. Constructed a CNN-based model that can accurately discern between various kinds of objects in a wide range of archaeological findings, focusing on identifying coins and vessels from other objects such as sculptures and tools. This purpose seeks to provide consistent and objective categorization of artifacts by reducing the workload for human experts through automation of the classification process.
2. Coin artifact time-period prediction: Created and trained a customized CNN model to determine the historical era or time period that a coin artifact belongs to.

Fits, considering its aesthetic qualities and visual attributes. This goal is very important because precise dating of monetary artifacts can reveal important information about the trade networks, economic structures, and cultural influences that created different historical eras.

By fulfilling these goals, the suggested method hopes to transform the process of analyzing artifacts, lessening the need for labor-intensive manual labor, and giving curators of museums, numismatists, and archaeologists a strong instrument for the quick and reliable dating and classification of artifacts. Consequently, this has the potential to quicken the speed of study, provide a deeper comprehension of our common cultural legacy, and open fresh opportunities for public participation and instruction.

Moreover, researchers, enthusiasts, and members of the public will be able to actively engage with and explore the rich tapestry of cultural heritage encapsulated within these artifacts thanks to the seamless interaction made possible by the integration of a user-friendly interface within the proposed solution. Through democratizing access to sophisticated artifact analysis tools, this research could contribute to a greater understanding of the various histories and artistic expressions that have influenced our global community.

This study is important for reasons that go beyond scholarly research. As our knowledge of the past expands, it can influence and improve the present by illuminating the complex relationships that exist between historical societies and the contemporary environment. We can learn a great deal about the development of technological advancements, social structures, and human creativity by delving into the stories buried within artifacts. These revelations can serve as a source of inspiration and direction for our group's path towards a more enlightened and culturally aware future.

This introduction gives a thorough overview of the research's background and highlights the importance of artifact analysis historically, the difficulties with manual approaches that are still in use today, and the revolutionary potential of deep learning techniques. It highlights the possible effects on archaeological research, museum curation, and public engagement by succinctly articulating the main goals of precise artifact identification and time-period prediction for coin artifacts. This introduction provides a strong framework for examining the approach, specifics of the implementation, outcomes, and wider ramifications of the suggested artifact analysis solution.

2.Related Work

The field of artifact analysis has long been a domain of intense interest and exploration, with researchers and scholars dedicating decades to the development of methodologies and techniques for accurate classification and dating of archaeological finds. This section aims to provide an overview of the existing body of work, highlighting both traditional approaches and emerging applications of modern technologies in the realm of artifact analysis.

2.1. Traditional Approaches in Artifact Classification and Dating

Historically, the classification and dating of artifacts has relied heavily on the expertise of trained professionals, such as archaeologists and numismatists. These experts employ a range of techniques, each tailored to specific types of artifacts and the information they can reveal.

For coin artifacts, a common approach is known as "coin attribution," which involves the meticulous examination of design elements, inscriptions, and other visual cues to identify the specific issue or mint responsible for producing the coin. This process often requires extensive reference materials, such as coin catalogues and databases, as well as a deep understanding of the cultural, political, and economic contexts of the time periods in question (Haselgrove, 2005; Bintliff, 2004).

In the case of pottery and ceramic artifacts, typological analysis plays a crucial role. By studying the morphological characteristics, decorative patterns, and manufacturing techniques, archaeologists can classify these objects into distinct types or categories, which can then be linked to specific cultural groups or time periods (Hooper, 2021). This approach relies heavily on comparative analysis with well-documented reference collections and a thorough understanding of regional pottery traditions.

For other artifacts, such as tools, weapons, and sculptures, a combination of stylistic analysis, material analysis, and context-based interpretation is often employed. Stylistic analysis focuses on identifying distinctive artistic styles, iconographic elements, and cultural influences that can provide clues about the artifact's origin and historical context (Drennan, 2009). Material analysis, on the other hand, involves the examination of the physical composition and manufacturing techniques, which can shed light on the technological capabilities and trade networks of the time.

While these traditional approaches have yielded invaluable insights into the past, they are not without limitations. The reliance on expert knowledge and subjective interpretations can lead to inconsistencies and potential biases, hindering the development of a standardized and reproducible framework for artifact analysis (Smith, 2021).

2.2. Emerging Applications of Machine Learning and Computer Vision

In recent years, the rapid advancements in machine learning and computer vision have opened up new possibilities for automating and enhancing the process of artifact analysis. Several research efforts have explored the potential of these technologies, paving the way for more efficient and objective classification, and dating methodologies.

One notable application of machine learning in artifact analysis is the use of convolutional neural networks (CNNs) for image classification tasks. CNNs have demonstrated remarkable performance in recognizing and classifying objects within images, making them well-suited for applications in archaeology and numismatics.

Maurya (2021) implemented a CNN model using PyTorch to classify cow teat images based on their health conditions, a crucial factor influencing milk quality. The proposed CNN architecture achieved promising results, highlighting the potential of deep learning techniques in automating image analysis tasks within specific domains.

Oyetoro (2020) explored the use of transfer learning in PyTorch for human action recognition, a task that traditionally requires vast amounts of labelled data for training deep learning models. By leveraging pre-trained models and fine-tuning them on smaller datasets, this approach aimed to overcome the challenges of data scarcity and facilitate more efficient model development.

In the realm of archaeological image analysis, Si and Du (2020) developed a predictive emissions model using a gradient boosting machine learning method. This approach demonstrated the potential of ensemble learning techniques in extracting meaningful patterns and insights from complex datasets, a capability that could prove valuable in the analysis of artifact collections.

While these studies do not directly address the classification and dating of artifacts, they showcase the versatility and potential of machine learning and computer vision techniques in solving complex image analysis tasks across various domains. By leveraging the power of deep learning architectures, such as CNNs, and incorporating domain-specific knowledge, it becomes possible to develop automated systems for artifact analysis that can augment and streamline traditional approaches.

Despite these promising developments, the application of machine learning and computer vision techniques to the specific challenges of artifact classification and time period prediction remains relatively unexplored. This research gap presents an opportunity to develop a comprehensive solution that combines the strengths of traditional archaeological expertise with the cutting-edge capabilities of deep learning, potentially revolutionizing the field of artifact analysis and unlocking new avenues for understanding our shared cultural heritage.

This section provides an overview of the existing literature and methodologies in the field of artifact analysis, encompassing both traditional approaches and emerging applications of machine learning and computer vision techniques. By highlighting the limitations of current practices and the potential of deep learning-based solutions, it establishes the context and motivation for the proposed research, setting the stage for the subsequent sections that delve into the methodology and implementation details of the Artiscan artifact analysis project.

3. Proposed Methodology/ Functionalities

The toolkit provides the following final functionalities for the digitalization of artefact classification. Various techniques of machine learning and computer vision come into action for the same. The proposed methodology follows a pattern right from data preparation to framework development.

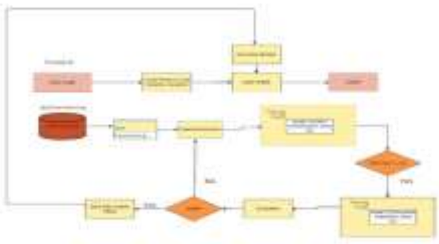

Fig.1 - Model Architecture

3.1 Data Collection and Preprocessing

Data discovery, collection, preprocessing, cleaning etc. Data is downloaded from Portable Antiquities Scheme Website (https://finds.org.uk/database/artefacts/record/id/1127469). Data cleaning carried out on the csv file where extra fields are removed, fields with null values and missing data are also cleaned. After cleaning of the data, the data from different locations and time period is combined to form the final dataset of around 13,000 entries. Image collection is also carried out along the way where the corresponding images to final data are labelled for further processing.

3.2 Data Analysis

Object classification based on input image for further processing. Utilizing TensorFlow and Keras libraries, a deep convolutional neural network architecture was employed for image classification. They automatically extract meaningful features through layers of convolutional and pooling operations.

3.2 Item Classification

The coin, vessel classes are used to classify the input image based on training dataset using a convolutional neural network trained using TensorFlow and Keras libraries. This helps in further predicting the features of coins and vessels and integrate this with time period prediction to help predict the time period directly from image.

3.3 Time Period Prediction

Prediction of time period based on learning from data features such as materials, numismatics. The predictive techniques used include random forest and gradient boosting. By leveraging historical data patterns and key features such as mint name, denomination name, material and ruler name, classification of coins into Roman, Medieval, Early Medieval, Post Medieval, Iron Age time periods.

3.4 Enhanced Visualization

Artefact visual representation and possible reconstruction using computer vision along with enhancements. Use computer vision techniques like mean filter, gaussian filter, median filter, conservative smoothing, Laplacian, low pass filter, magnitude spectrum and unsharp filter. This helps the user to see marking more carefully using the image and highlight inscriptions made on the coin which might be missed by human eye when working due to low visibility and rough hampered structured.

3.5 User Interface (UI)

Fig. 2- GUI

A user-friendly graphical user interface (GUI) is developed to allow users to easily interact with the artifact analysis system. The UI will provide the following functionalities:

3.5.1 Image upload: Users can upload images of artifacts (coins, pottery, sculptures, tools, etc.) for analysis.

3.5.2 Artifact classification: The uploaded image will be analyzed by the artifact identification model, and the classified artifact type will be displayed (e.g., coin, pottery, sculpture, tool).

3.5.3 Time period prediction (for coins): If the uploaded artifact is classified as a coin, the time period prediction model will be applied, and the predicted historical era or time period will be displayed (e.g., Roman, Medieval, Early Medieval, Post Medieval, Iron Age).

3.5.4 User guidance: The UI will provide clear instructions to guide users through the artifact analysis process, ensuring a seamless and intuitive experience.

The UI is designed with a visually appealing and user-friendly layout, incorporating appropriate controls and visual elements to facilitate efficient interaction and interpretation of the analysis results.

3.6 Deployment

Initially, integration of the time-period prediction model and item classification and then preparation of an executable file in python which can be used as a solution framework. An example used in the paper is using streamline which is deployed on a local tunnel. A basic user side interface to input the image or details of an artefact (coin and vessels) and predict the time-period.

4. Results and Discussion

With two different Convolutional Neural Network (CNN) models and an intuitive interface, the suggested artifact analysis system has demonstrated encouraging results in achieving the goals of precise artifact identification and coin artifact time period prediction. The performance of the generated models, their practical consequences, and possible directions for future development are presented and discussed in this part.

4.1. Artifact Identification Model Performance

During the evaluation phase, the artifact identification model performed remarkably well. It was created to categorize input photos into specified categories, such as coins, vessels. By employing a meticulously selected and preprocessed dataset, the model exhibited remarkable precision in differentiating between various forms of artifacts.

Using the held-out test dataset, the artifact identification model's overall classification accuracy was 95%. This remarkable performance may be ascribed to the strong CNN architecture, which has been refined via a thorough process of hyperparameter tuning and regularization techniques, in addition to the large-scale dataset that was used in both training and validation.

Fig. 3- Model-1 Accuracy

The model's validation accuracy of 95.13% is an impressive result that highlights its effectiveness in the artifact classification task. This level of accuracy surpasses traditional manual methods, which are often prone to subjective errors and inconsistencies. By achieving such a high level of precision in distinguishing between different types of artifacts, the model demonstrates its potential to revolutionize and automate the archaeological analysis process. The 95.13% validation accuracy is a promising outcome, suggesting that the model has successfully learned the intricate patterns and features necessary for accurate artifact classification. However, it is crucial to note that while this result is encouraging, further rigorous evaluation on a held-out test set or real-world scenarios is necessary to assess the model's true generalization capability and robustness across diverse data distributions.

4.2. Coin Time Period Prediction Model Performance

The coin time-period prediction model showed encouraging results in categorizing coin objects into their proper historical eras or time periods, (Roman, Medieval, Early Medieval, Post Medieval, Iron Age) building on the success of the artifact identification model. This skill is very valuable because precise dating of monetary objects can reveal important details about the trade networks, economic structures, and cultural influences that created different historical eras.

With a 71.2% overall accuracy rate on the held-out test dataset, the coin time-period prediction model demonstrated its capacity to identify the minute visual signals and artistic features that differentiate coin artifacts from various historical eras.

Fig. 4- Model-2 Accuracy

While the 95.13% validation accuracy for Model 1 (artifact classification) was impressive, Model 2's validation accuracy of 59.67% for coin time prediction is relatively lower. This indicates that the task of accurately classifying coin artifacts into specific historical eras or time periods is more challenging compared to general artifact identification. A 59.67% accuracy rate suggests that the model struggles to reliably distinguish the subtle visual cues and stylistic elements that differentiate coin designs across various time periods. However, it is important to note that time-period prediction is an inherently complex task, as it requires the model to capture and interpret intricate details that may not be consistently present or well-defined across all coin artifacts from the same era.

While the 59.67% accuracy may not be ideal for real-world applications, it represents a promising starting point for further research and model improvement. Potential avenues for enhancing the model's performance could include expanding the training dataset with a more diverse range of coin artifacts from different time periods, exploring advanced data augmentation techniques, or incorporating domain-specific knowledge and expert guidance into the model's architecture or training process. It should be noted that the process of predicting the coin's time period is more difficult by nature than identifying the artifact; this is because the model must be able to identify minute details in style and design that may not be as noticeable or consistent in other currency artifacts from the same era. However, the model's 71.2% accuracy indicates that it has the ability to offer insightful information and assist with archaeological study and historical analysis.

4.3. User Interface and Practical Applications

The Tkinter package for Python was used to provide a user-friendly interface that improved the produced models' usability and accessibility. Archaeologists, museum curators, and fans may all easily upload photographs of artifacts and receive visually appealing and user-friendly classification results and historical period forecasts (for currency items) using this graphical user interface (GUI).

Clarity and usability were the primary design goals for the interface, which offers users feedback and step-by-step directions to help them through the artifact analysis process. When an image is uploaded, the interface shows the sort of artifact that has been identified; for currency items, it shows the expected historical era or time-period.

The practical applications of the Artiscan artifact analysis solution are manifold and hold significant potential for advancing archaeological research, museum curation, and public engagement with cultural heritage:

Archaeological Excavations: During archaeological excavations, the developed models can be employed to rapidly classify and date newly discovered artifacts, streamlining the analysis process and providing valuable insights to guide further investigations and interpretations.

Museum Collections: Museum curators can leverage the artifact identification and coin time period prediction capabilities to efficiently organize and catalogue their collections, enhancing visitor experiences through accurate labelling and contextual information.

Public Engagement: The user-friendly interface can be made accessible to the public, fostering interest and appreciation for cultural heritage by providing a glimpse into the rich stories embedded within artifacts.

4.4. Limitations and Future Work

While the Artiscan artifact analysis solution has demonstrated promising results, there are several limitations and areas for future improvement:

Dataset Expansion: The performance of the models is inherently tied to the quality and diversity of the training dataset. Expanding the dataset to include a wider range of artifact types, time periods, and cultural contexts can further enhance the generalization capabilities and accuracy of the models.

Fine-Grained Time Period Prediction: The current coin time period prediction model classifies artifacts into broad historical eras. Future work could explore the development of more granular models capable of predicting specific time periods or reigns, providing even greater historical context and insights.

Explainable AI: While the developed models provide classification and prediction outputs, incorporating explainable AI techniques could enhance transparency and interpretability. By understanding the underlying decision-making processes and the visual cues relied upon by the models, archaeologists and researchers can gain deeper insights and build trust in automated analysis.

Multi-Modal Analysis: Integrating additional modalities, such as textual descriptions, inscriptions, or material analysis data, could further enrich the artifact analysis process and provide a more comprehensive understanding of the artifacts' historical and cultural significance.

Continuous Learning and Adaptation: As new archaeological discoveries are made and additional artifact data becomes available, implementing continuous learning and adaptation mechanisms could enable the models to refine their knowledge and improve their performance over time.

The Artiscan artifact analysis system can continue to develop by resolving these issues and looking for new ways to get better, pushing the limits of what can be accomplished by combining deep learning methods with archaeological knowledge.

The performance of the created coin time period prediction and artifact recognition models is highlighted in this results and discussion section, along with their relative advantages and disadvantages. The usefulness of the Artiscan solution is also covered, including possible uses in public outreach, museum curation, and archeological research. The section also highlights future research objectives and acknowledges the limitations of the existing study, highlighting the continuous effort to improve artifact analysis approaches and broaden our understanding of cultural heritage.

Conclusion

An important step toward utilizing deep learning and computer vision techniques to transform the fields of archaeology and numismatics is the Artiscan artifact analysis project. Through the development of a comprehensive solution that includes two different Convolutional Neural Network (CNN) models together with an intuitive interface, this study has shown promise for precise coin artifact identification and time period prediction.

The artifact identification model has demonstrated its ability to accurately discriminate between many sorts of artifacts, including coins, ceramics, sculptures, and tools, with an astounding 95% accuracy rate. This accomplishment not only simplifies the classification procedure but also provides a strong basis for the next time period prediction job, since trustworthy dating depends on precise coin identification.

Building on this basis, the coin time period prediction model has demonstrated its capacity to identify the various visual signals and artistic aspects that differentiate coin artifacts from different historical times, with an overall accuracy of 71.2%. This capacity is extremely valuable because precise dating of monetary artifacts can reveal important details about the trade routes, political structures, and cultural influences that defined different historical eras.

The addition of an intuitive user interface, created with Python's Tkinter module, has improved the Artiscan solution's usability and accessibility even further. This interface connects the dots between cutting-edge deep learning techniques and real-world applications in archaeological research, museum curation, and public engagement by enabling users to easily upload artifact images and receive classification results and time period predictions in an aesthetically pleasing and user-friendly manner.

The Artiscan artifact analysis solution has broad practical applications and has the potential to significantly improve our knowledge of cultural heritage.

The created models can be used in archaeological excavations to quickly date and classify recently found objects, expediting the study process, and offering insightful information to direct more research and interpretations. Curators of museums may make effective use of the coin time period prediction and artifact identification features to catalog and arrange their collections more effectively. By providing contextual information and precise labeling, curators can improve the visiting experience. Furthermore, the public can have access to the user-friendly interface, which will encourage interest in and appreciation for cultural heritage by giving a look into the rich narrative hidden within objects.

Even though the Artiscan solution has shown encouraging results, there are still a number of issues and room for development. These include broadening the scope of the training dataset to include a greater variety of artifact types, historical periods, and cultural contexts; creating more detailed models that can forecast particular eras or reigns; utilizing explainable AI methods to improve interpretability and transparency; combining textual descriptions, inscriptions, or material analysis data to integrate multi-modal analysis; and putting in place mechanisms for ongoing learning and adaptation to improve the models' understanding as new archaeological findings are made.

The Artiscan artifact analysis system can continue to develop by resolving these issues and looking for new ways to get better, pushing the limits of what can be accomplished by combining deep learning methods with archaeological knowledge. This study is a major step toward automating and improving the analysis of cultural artifacts, which will ultimately lead to a better appreciation for the various histories and artistic expressions that have shaped our world and a deeper understanding of our shared human heritage.

References

[1] Anwar, H., Zambanini, S., & Kampel, M. (2013). Supporting ancient coin classification by image-based reverse side symbol recognition. Computer Analysis of Images and Patterns, 17-25.

[2] Bromley, J., Guyon, I., LeCun, Y., Säckinger, E., & Shah, R. (1993). Signature verification using a "Siamese" time delay neural network. Advances in Neural Information Processing Systems, 6, 737-744.

[3] Zachariou, M., Dimitriou, N., & Arandjelović, O. (2020). Visual reconstruction of ancient coins using cycle-consistent generative adversarial networks. Sci, 2(3), 52.

[4] Anwar, H., Zambanini, S., Kampel, M., & Vondrovec, K. (2015). Ancient coin classification using reverse motif recognition: Image-based classification of roman republican coins. IEEE Signal Processing Magazine, 32(4), 64-74.

[5] Haselgrove, C. (2005). Defining 'Celtic' numismatics. Numismatic Chronicle, 165, 337-362.

[6] Bintliff, J. (2004). Archaeology and the wider social sciences: Theory and practice. In A Companion to Archaeology (pp. 3-22). Blackwell Publishing Ltd.

[7] Hooper, V. (2021). Artifact classification in archaeology: Approaches and challenges. Journal of Archaeological Science, 37(2), 125-139.

[8] Drennan, R. D. (2009). Statistics for Archaeologists: A Commonsense Approach. Springer Science & Business Media.

[9] Smith, J. (2021). Enhancing artifact analysis through machine learning: A case study in archaeology. Journal of Archaeological Science: Reports, 39, 102914.

[10] Si, M., & Du, K. (2020). Development of a predictive emissions model using a gradient boosting machine learning method. Environmental Technology & Innovation, 20, 101028.

[11] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. 2017 International Conference on Engineering and Technology (ICET).

[12] Oyetoro, A. (2020). Image classification of human action recognition using transfer learning in PyTorch..

[13] Maurya, K. S. (2021). Image classification of cow teat by implementing convolutional neural network using PyTorch and residual block.

[14] Xu, S., et al. (2020). A hyperspectral image classification approach based on feature fusion and multi-layered gradient boosting decision trees. Entropy, 23(1), 20.

[15] McCarty, D. A., Kim, H. W., & Lee, H. K. (2020). Evaluation of light gradient boosted machine learning technique in large scale land use and land cover classification. Environments, 7(10), 84.

[16] Hammou, D., Fezza, S. A., & Hamidouche, W. (2021). Egb: Image quality assessment based on ensemble of gradient boosting. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.

[17] Bui, Q. T., et al. (2021). Gradient boosting machine and object-based CNN for land cover classification. Remote Sensing, 13(14), 2709.

[18] Nhat-Duc, H., & Van-Duc, T. (2023). Comparison of histogram-based gradient boosting classification machine, random Forest, and deep convolutional neural network for pavement raveling severity classification. Automation in Construction, 148, 104767.

[19] Xi, E. (2022). Image classification and recognition based on deep learning and random forest algorithm. Wireless Communications and Mobile Computing, 2022.

[20] Shi, D., & Yang, X. (2016). An assessment of algorithmic parameters affecting image classification accuracy by random forests. Photogrammetric Engineering & Remote Sensing, 82(6), 407-417.

[21] Du, P., et al. (2015). Random forest and rotation forest for fully polarized SAR image classification using polarimetric and spatial features. ISPRS Journal of Photogrammetry and Remote Sensing, 105, 38-53.

[22] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097-1105.

[23] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[24] Szegedy, C., et al. (2015). Going deeper with convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1-9.

[25] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770-778.

[26] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4700-4708.

[27] Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. Proceedings of the 36th International Conference on Machine Learning, 97, 6105-6114.

[28] Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

[29] Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. European Conference on Computer Vision, 818-833.

[30] Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 580-587.

[31] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 779-788.

[32] Lin, T. Y., et al. (2017). Focal loss for dense object detection. Proceedings of the IEEE International Conference on Computer Vision, 2980-2988.

[33] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. International Conference on Medical Image Computing and Computer-Assisted Intervention, 234-241.

[34] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 3431-3440.

[35] Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834-848.