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Deep Insights with Exploring Plankton Communities through Artificial Neural Networks

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Abstract
The separation and categorization of marine species are of great significance for determining which interact differently among themselves and whether such interaction influences the maintenance of biodiversity in the marine ecosystem. In this study, we present a comparative analysis of various artificial intelligence (AI) models applied to the classification of images of two distinct types of polychaeta: Polychaeta species Type A and Type F. Applying a dataset holding annotated images of polychaeta type subdivision, we experience the effective AI architectures, e.g., CNNs and others, in the process of precise identification of these species. By means of methodology, we will process the image dataset and then train and evaluate different AI models on the sorted photos that were selected. The model metrics are evaluated, and the evaluation is based on the accuracy and the epoch for each model type. Moreover, through the study of the models' decisions' interpretability, we draw a darker picture of the essence of the classification processes. The result of our study has been decisive; it has indicated the advantages and disadvantages of each AI model when inspecting Type A and Type F

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DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

polychaeta. Moreover, we consider the bearing of the result obtained on marine ecology research and highlight the prospect of AI-based image classification techniques in providing remote and real-time monitoring, subduction, and study of underwater biodiversity. This research moves forward with the efforts of artificial intelligence techniques in ecological studies, which further show how the combination of different disciplines can be used to solve problems of marine science and conservation.
Index Terms— AI; CNN; Classification

Introduction

Variety of organisms such as fish, corals reefs, plants and many more find their niche in the marine ecosystems and ensure that a given system is in a healthy and viable state. Natural communities of microorganisms' diversity contain many polychaetes, a highly diverse group of the marine worms living worldwide underwater. Species interact with each other and from their interaction the ecosystem details emerge against the background of which conservation and restoration works are made.

Conventional recognition of sea species used to be a heavily manual based process that was time consuming due to its dependence on the knowledge of taxonomy experts.

Nevertheless, the emergence of artificial intelligence (AI) and machine learning (ML) strategies as automation and optimization means has brought novel and exciting paths to address this task. How AI helped in image classification is within the scope of the work of AI in rapidly and accurately identifying various marine species within individual visual characteristics.

In this context, the present study focuses on the application of different AI models for the classification of images of a specific type of polychaeta: Type-A and type-F. These are the two main types of polychaeta that are known to display different morphological characteristics and area of suitability. As such, they are considered quite adequate for comparison using an AI-based classification method.

Problem Statement

Although polychaeta worms fill many roles in seas and¨ aquatic ecosystems, the assignation of various species is difficult. Hand drawings are usually tedious, consuming a lot of time, and filled with mistakes of individuals, so they have disadvantages in the complete studies of polychaeta diversity and pattern. In addition, polychaeta features substantial intraspecies characteristics as well as interspecies ones which adds to the need for automated classification procedures that are accurate.

The last few years have been characteristic of the principles of artificial intelligence (AI) and machine learning (ML) which have proposed solutions for the classification of marine organisms based on the data provided by images. On the other side, the AI techniques used for sorting Polychaetae, for instance, into Type A and Type F, involve their own set of difficulties. A range of hurdles are faced by researchers including the diversity of polychaeta bodies, the requirement of large and properly annotated image datasets [1] as well as the identification of ideal AI architecture for successful recognition.

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DIALOGUE SOCIAL SCIENCE REVIEW

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Therefore, the problem addressed by this research paper is twofold: firstly, to evaluate the performance of AI techniques for recognizing type A as well as type F Polychaeta images, and secondly, to highlight the power and limitations of these techniques in the field of marine ecology research. The investigation is intended to give a boost to the creation of automated classification methods dedicated to this group of polychaeta, which, in turn, will expedite the studies of marine biodiversity and ecosystems.

Research Motivation

As the global population continues to rise, it raises the need for our knowledge of marine biodiversity and ecosystem concerns unique for polychaeta worms to keep advancing. They (the polychaeta ships) are vital links in the trophic cycle, nutrient distribution, human decision-making, and the overall health of the marine ecosystems. Nevertheless, the precise segregation and determination of polychaete species is exceedingly difficult and hinders in-depth ecological surveys and efforts to conserve marine biodiversity.

Manual identification methods although useful, are often challenging and constrained by their highly technical nature and expertise involving making precise species classifications. In addition, inconspicuous gradual variations in the characteristics of polychaetes demonstrate the well-known intricacies in their classification. It may be due to this that a number of researchers are applying AI and ML more to classify marine organisms using data.

By applying AI models to the classification of Type A and Type F polychaeta, this research aims to address several key motivations:

1. Efficiency: The application of polychaeta classification AI models in automation will hasten analysis, enabling researchers to evaluate huge datasets in little time and with limited human capital and energy as compared to traditional manual methods as well as other AI models.
2. Accuracy: By harnessing the power of deep learning algorithms, we seek to achieve elevated levels of accuracy in distinguishing between Type A and Type F polychaeta to provide reliable data for ecological studies and conservation initiatives.
3. Scalability: AI-powered categorization processes can accommodate various marine territory types, bringing the ability to investigate large-scale geo-diversity and track the population changes of polychaetes over time.
4. Interpretability: Learning the processes of decision making of AI models for polychaeta classification is a good knowledge tool as it helps us understand the traits and shapes that define marine ecology and evolution.

I. CONTRIBUTIONS

To get round the issues discussed in the previous sections, this paper proposes and compares AI models, namely CNN, Multi-Layer Perceptron (MLP) and ResNet50 to gain valuable insights into a range of domains:

1. Evaluation of AI Models: We provide a comprehensive evaluation of various artificial intelligence (AI) models, including convolutional neural networks (CNNs) and deep learning architectures, for the classification of images of Type A and Type F

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DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

polychaeta. Our analysis sheds light on the performance, strengths, and limitations of each model in accurately distinguishing between these two polychaeta types.

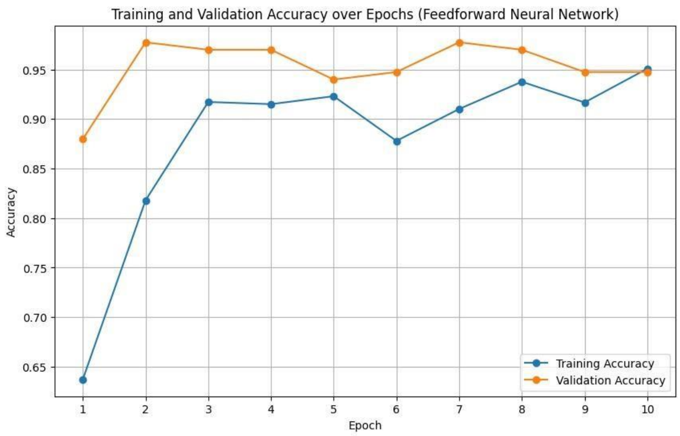

Fig. 1. Training and Validation Accuracy over Epochs (Feedforward Neural Network)

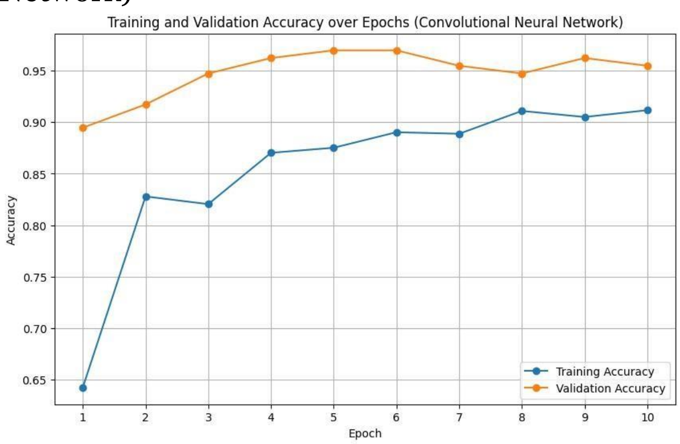

Fig. 2. Training and Validation Accuracy over Epochs (Convolutional Neural Network)

2. Benchmark Dataset: We contribute to the research community by curating and annotating a benchmark dataset of images containing Type A and Type F polychaeta specimens. This dataset serves as a valuable resource for training and testing AI models for polychaeta classification and can facilitate further research in marine ecology and biodiversity assessment.

3. Implications for Marine Ecology Research: Our findings have implications for marine ecology research, demonstrating the potential of AI-driven image classification techniques in studying marine biodiversity and ecosystem dynamics. By automating the classification of polychaeta species, researchers can efficiently analyse large-scale datasets and uncover patterns that inform conservation strategies and ecosystem management practices.

5. Interdisciplinary Collaboration: This research fosters interdisciplinary collaboration between marine scientists, computer scientists, and conservation biologists. By bridging

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Vol. 2 No. 5 (December) (2024)

these disciplines, we facilitate knowledge exchange, innovation, and the development of holistic approaches to addressing complex.

Fig. 3. Comparison of Training and Validation Accuracy over 10 Epochs for ResNet50 Model

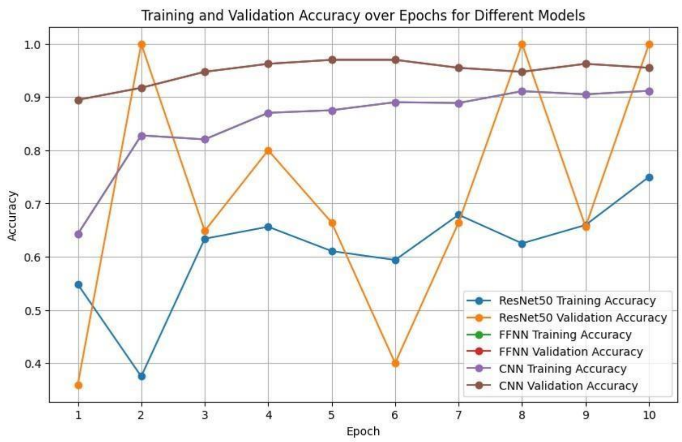

Fig. 4. Training and Validation Accuracy over Epochs for Different Models
challenges in marine biodiversity conservation.

Literature Review

In [2], the authors have developed a system to capture the images of various plankton types. Plus, they have also implemented a classification system based on multiclassification ResNet-18 and reclassification VGGNet-11. Not only this they have also took help from domain experts to label the images under their supervision. An imager at the sea sends the captured images to a server from where data is taken for.

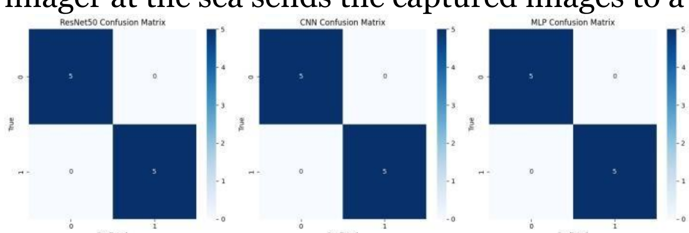

Fig. 5. Confusion Matrix Fig. 6. Workflow

further processing. This paper mainly focuses on collection and labelling of plankton dataset.

In [3], the authors have made a new type of an imager to capture the images of planktons. They further say that in a period of three years they have collected 2,500,000 images. Out of these images 20,000 images were identified by humans. Manually identified images were divided in forty-three unique folders. They used hybrid CNN model to classify the other images. Accuracy of their model varied in different classes. To improve model different advance techniques were used.

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ISSN Online: 3007-3154
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Vol. 2 No. 5 (December) (2024)

In [4], authors have suggested a method to save the disk space available onboard with an imager. Since imager takes a larger number of images every day. The onboard disk can get full very rapidly and it is not feasible to change or access it regularly. For this purpose, authors have written a program which only send those images which are important. To make system more efficient a real time processing board was also added to preprocessor the data. Due to which now system needs less memory and bandwidth.

In [5], the researchers have utilized clustering technique to make clusters of unlabelled images of plankton. For this purpose, they used a number of advanced and modern techniques. t-SNE projection was done to get the 2D clusters of the plankton. Development of this technique has helped in the classification of plankton through image dataset.

Study of plankton particle size was done in [6]. Instead of using images to do analysis, a video based real time solution was implemented to study plankton particle size. It was done to study plankton as they are vital for life on earth. Without plankton particle, marine ecosystem will collapse.

In [7] the author has purposed a new technique to improve the previous data classification techniques which are based on expectation theory of the mathematics. This work is done on spatial data. This technique is developed to solve the complex problems of the big data or big dataset. In the end author say that piratical work was done, and it was found that new technique is better than the previous one.

In [8], the authors have worked on a Deep Pyramidal Residual Networks to classify the plankton. This approach is also known as Pyramid. Pyramid is based on a Deep Convolutional Neural Networks (DCNNs) which was used to improve the classification process as manual classification was very time consuming. DCNNs have shown remarkable performance which is better than all the previous classification approaches. Outputs were compared against import benchmarks such as F1 score.

Ballast water transports the aquatic life during in the commercial shipping. In this paper [9] authors have tried to monitor the plankton during the transportation process. Large dataset is generated to monitor these plankton during shipment process. As a large number of images are taken from a very high-resolution camera. These images are extracted from the video from every frame. They used Visual Rhythm to count the plankton during the discharge of ballast water.

Plankton classification was done in [10]. The paper shows their implementation of end-to-end hybrid convolutional neural network had better output than the previously implemented model. They took can image dataset which had 3,600,000. These images were labelled into one hundred and three classes. The purpose of doing this research was to classify plankton to get better understanding of our biological ecosystem.

[11] applied a LightBGM to classify the plankton. A hybrid resample method was added to LightBGM classifier to improve the output. F1 and G means were used to evaluate the model which was implemented. Since plankton have imbalanced class distribution that is why this new technique was developed. It improved the accuracy of plankton classification on imbalance dataset.

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ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

In [12] researchers are using simulation to determine the plankton dynamics. It is focuses on how seasonal variation affect the dynamics of the plankton in Bay of Bengal. OAmethod and SOR-algorithm are used. For these models Satellite-derived chlorophyll-concentration data is used. Increase in fresh water can increase the plankton. Peak months are March and September.

The authors presented a hierarchical classification approach for polychaeta species identification, organizing species into taxonomic hierarchies to improve classification accuracy in [13]. Their study demonstrated promising results in discriminating between closely related polychaeta species. Having said that, the scalability of their approach to a broader range of polychaeta taxa and the potential biases introduced by hierarchical classification schemes warrant further investigation.

In [14] a three-dimensional model is used to show the effect of fresh water on plankton. Ocean colour monitor data is used for this purpose. It was done in the presence of tides and in the absence of high tide. The RMSE was below 0.6 which means model performs very well. As far as skill coefficients is concerned it was more than 0.80 which is quite good.

Artificial intelligence (AI) has managed to acquire image classification capabilities to its precision and scale which allows it to be able to analyze vast amounts of datasets such of the case of hidden patterns in marine biodiversity [15]. AI enhanced business intelligence draws focus on the need for a data-based approach which can be used for the supervision and research of organisms such as communities of plankton [16].

Scalable data lake infrastructures for IoT frameworks in systems implementing IoT shows the significance of proper handling and processing of large annotated marine databases [17]. The fact that AI has been employed in the provision of strategic direction in areas such as healthcare is indicative that it has the prospects of improving classification of model parameters in marine ecosystems [18]. Newer generation types of AI applications among them those that fuse quantum computers demonstrates the possibilities that abound for better classification of marine species [19].

The use of gradient boosting models in predictive analysis of weather forecasting brings to the fore the role that AI can play in ecosystems such as marine ecosystems that are prone to rapid changes [20]. AI powered approaches for load forecasting demonstrate that these types of methods can be beneficial in resource optimization during the training phase of neural networks on big marine resources [21]. In the case of constructing data lake-houses in cloud environments, emphasis is on appropriate data storage technologies that are vital in handling large amounts of images relevant to marine research [22].

Transformative AI in predictive analytics has demonstrated its value in deriving actionable insights, aligning closely with efforts to analyze and classify plankton communities [23]. Distributed AI tasks in cloud ecosystems provide a framework for handling the computational demands of deep learning models, a necessity for large-scale marine image classification projects [24].

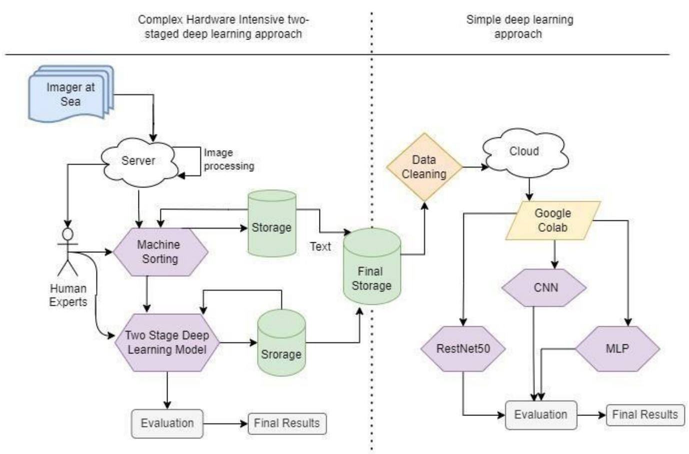
Dialogue Social Science Review (DSSR)
www.journalforeducationalresearch.online

ISSN Online: 3007-3154
ISSN Print: 3007-3146

Vol. 2 No. 5 (December) (2024)

II. PROPOSED METHODOLOGY

Research Design: At the core of our research design lies a comprehensive sampling strategy. Leveraging stratified sampling techniques, we systematically collect image data of Type A and Type F polychaeta specimens.



Data Collection and Preprocessing: Collect a diverse dataset of images containing Type A and Type F polychaeta specimens from various marine environments. Perform preprocessing steps such as image resizing, normalization, and augmentation to enhance the quality and diversity of the dataset. Annotate the images with ground truth labels indicating the polychaeta type (Type A or Type F) for supervised learning.

Model Selection and Training: Evaluate and select appropriate AI models for polychaeta classification, including convolutional neural networks (CNNs), deep learning architectures, and transfer learning approaches. Split the annotated dataset into training, validation, and testing sets to train and evaluate the selected models.

Performance Evaluation: Assess the performance of each AI model based on metrics such as accuracy and epoch. For each epoch, we have showcased accuracy, loss, accuracy value and loss value against each AI model to analyse in greater detail how quickly they get trained and the improvement in their accuracy with each epoch.

Analysis Techniques: Our analysis incorporates statistical inference techniques to assess the significance of observed differences or correlations within the dataset. Through hypothesis testing, regression analysis, and correlation analysis, we uncover meaningful relationships between polychaeta characteristics, environmental variables, and classification performance. These statistical insights inform our understanding of the ecological dynamics and drivers of polychaeta diversity in marine ecosystems.

Finally, we conduct a comparative analysis of different AI models, analysis techniques, and classification approaches to identify strengths, weaknesses, and areas for improvement. By benchmarking performance metrics and interpretability measures across different methods, we gain a comprehensive understanding of the relative merits

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www.journalforeducationalresearch.online

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

and limitations of each approach, guiding future research directions and practical applications.

Results

Model Comparison: Comparative analysis of different AI models revealed variations in performance and computational efficiency. While deep learning architectures such as convolutional neural networks (CNNs) excelled in capturing complex morphological features, simpler machine learning algorithms also demonstrated competitive performance, particularly when trained on handcrafted features or smallscale datasets.
Interpretability Analysis: Our investigation into the interpretability of AI models' decisions provided valuable insights into the morphological features driving polychaeta classification. Visualization techniques such as saliency mapping, feature importance scores, and activation maps shed light on the key characteristics influencing classification outcomes, enhancing our understanding of polychaeta diversity and ecology.
Generalization and Scalability: We observed that AI models trained on our dataset

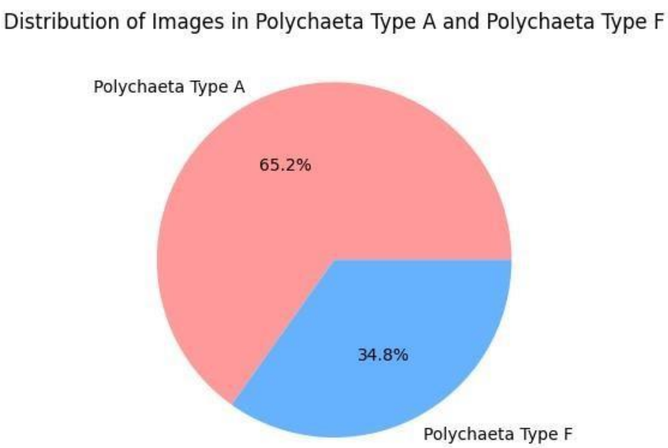
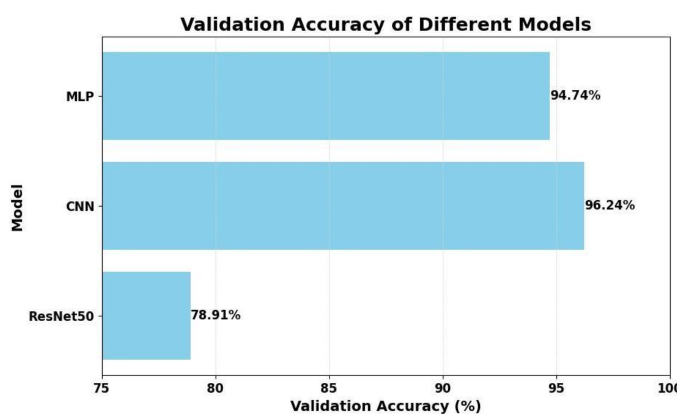


TABLE I
VALIDATION ACCURACY OF DIFFERENT MODELS



demonstrated robustness and general-
Fig. 7. Distribution of Images in Polychaeta Type A and Polychaeta Type F

Dialogue Social Science Review (DSSR)
www.journalforeducationalresearch.online

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

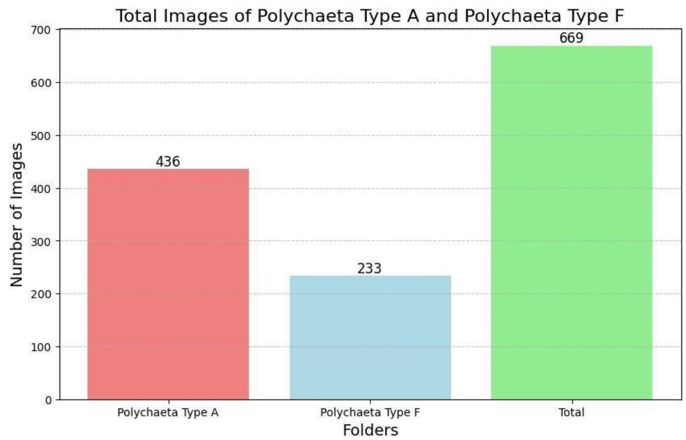


Fig. 8. Total Images of Polychaeta Type A and Polychaeta Type F

inability across diverse marine environments and polychaeta taxa. Transfer learning approaches proved effective in leveraging pre-trained models to classify polychaeta species with high accuracy, highlighting the scalability of AI-driven classification techniques to large-scale biodiversity assessments.

Results after testing for each model:

To maintain consistency in out testing, we used a standard number of 10 epochs for each model and a medium-sized dataset since CNN is already known to be more suited for large datasets while the other two are geared toward small datasets.

Model	Epoch used	Validation Accuracy (%)
ResNet50	10	78.91
CNN	10	96.24
MLP	10	94.74

Fig. 9. Validation Accuracy of Different Models

TABLE II: Resnet50 Model Results

Epoch	Training Accuracy	Validation Accuracy	Validation Loss
1	0.5482	0.3594	0.8204
2	0.3750	1.0000	0.3855
3	0.6337	0.6484	0.6169
4	0.6562	0.8000	0.4859
5	0.6105	0.6641	0.5674
6	0.5938	0.4000	0.7122
7	0.6787	0.6641	0.5528
8	0.6250	1.0000	0.6279
9	0.6595	0.6562	0.5574
10	0.7500	1.0000	0.4712

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www.journalforeducationalresearch.online

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

TABLE III: Convolutional Neural Network Model Results

Epoch	Training Accuracy	Validation Accuracy	Validation Loss
1	64.23%	89.47%	0.2075
2	82.79%	91.73%	0.1954
3	82.04%	94.74%	0.1457
4	87.03%	96.24%	0.1296
5	87.52%	96.99%	0.1174
6	89.03%	96.99%	0.1178
7	88.88%	95.49%	0.1304
8	91.10%	94.74%	0.1182
9	90.51%	96.24%	0.1038
10	91.17%	95.49%	0.1326

TABLE IV: Simple Feedforward Neural Network Model Results

Epoch	Training Accuracy	Validation Accuracy	Validation Loss
1	63.72%	87.97%	0.3191
2	81.79%	97.74%	0.1329
3	91.72%	96.99%	0.0861
4	91.50%	96.99%	0.0893
5	92.30%	93.98%	0.1735
6	87.79%	94.74%	0.1318
7	91.01%	97.74%	0.0753
8	93.76%	96.99%	0.0819
9	91.67%	94.74%	0.0895
10	95.08%	94.74%	0.1233

Conclusion and Future Work

In this investigation, we trained and tested three types of models which are ResNet50, CNN, finally MLP, on the dataset that we made. Models went through the same number of 10 epochs, and their accuracy was evaluated using validation accuracy.

It can be seen from the results that the accuracy score of the CNN model reached ninety-six. The MLP model reached 94 percent, the CNN model achieved 91 percent, and the convolutional network model reached 90 percent. The ResNet50 had a validation accuracy of 78 percent while the VGG16 model only managed 74 percent. In other words, ResNet50 performed.

better. 91

Although the CNN and MLP models are unachievable, they turn out to be the best approximation for our classification tasks and outperform the ResNet50 model. CNN demonstrated the best results. The fact that it implies spatial hierarchies in information through convolutional layers could be the reason.

However, it is important to note that these results underscore the importance of choosing the right class of models for tasks. Like CNN and MLP, the deep learning models have proved to be an edge, but extensive studies are need as one more

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www.journalforeducationalresearch.online

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 2 No. 5 (December) (2024)

architecture, image augmentation techniques, and model fine-tuning strategies may be worth their salt. Our next significant undertaking is dealing with the issue of the deployment and scale up of the trained models in real-world scenarios which requires further research.

In short, this study makes useful contributions on the demand for deep learning algorithm models for classification job which others can build on to explore more on this area of research.

In future research, several avenues could be explored to further enhance the performance and robustness of the models:

Exploring Additional Models: Exploit and assess additional variants of machine learning and deep learning models i. e. VGG, Inception and DenseNet on the same dataset to discover better diagnosis with higher accuracy. This will be more of a thorough analysis of architectures of assorted designs with a particular focus on the best performance depending on the task given.

Data Augmentation Techniques: Invite the repercussion of various data augmentation methods like rotation, scaling, flipping on model performance study. Data augmentation can assist in the increase of the model's generalization by including representations of real-world conditions to the training dataset and not only by training the model with only existing, available data.

Hyperparameter Tuning: Design a comprehensive evaluation of model hyperparameters in a systematic way with tuning experiments regarding model architecture, learning rate, batch size and regularization techniques. The applications of this process can be for further development of the models to hit their peak performance.

Ensemble Learning: Have a look at the ensemble learning techniques that are used to find the median of the population of the multiple models, and it increases the overall performance. Ensemble of techniques of bagging, boosting, and stacking, commonly, results in more successful outcomes, and is often superior to the individual models.

Transfer Learning: Study the strategy of using transfer learning by how you can use the already trained models on the target dataset. Transfer learning brings together demonstrated experience from source domain to up the performance in target domain, which is based on fewer labelled samples.

Interpretable Models: Design machine learning algorithms to be easily interpretable, so the process decision-making becomes transparent.

The participants gave positive feedback about the workshop. Many of them appreciated the approach that we took of having a balance between theory and practical implementation. Some others expressed their satisfaction with the range of practical exercises that we included in the workshop. One participant, specifically, mentioned that the virtual environment allowed them to learn at their own pace, decreasing the pressure Techniques such as SHAP (Shapley Additive Explanations) values and LIME (Local Interpretable Model – agnostic Explanations) are useful in the sense that they could help in understanding model predictions.

Deployment and Scaling: Research ways of implementing the trained models and at scale in the real apps. It encompasses the possibility of tuning the model inference speed, using models at edge devices, and achieving the scalability leak to manage the large volumes of data.

Through the consideration of these subjects of improvement, we would be able to make considerable progress with the machine learning models in this area which includes performance efficiency as well as interpretability and helpfulness in the real-world environment.

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Vol. 2 No. 5 (December) (2024)

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