International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6972
***Article Received**: 28 March 2023 **Revised**: 12 May 2023 **Accepted**: 24 May 2023*

Efficient Microalgae Species Identification using Compact Convolutional Neural Network

Rajmohan Pardeshi[1], Prapti Deshmukh[2]
[1]Department of Computer Science and Information Technology
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad , India
e-mail: madhurrajmohan1@gmail.com
[2]Dr. GY Pathrikar College of Computer Science and Information Technology
MGM University, Aurangabad , India
e-mail: prapti.research@gmail.com

Abstract—In this study, we propose a novel approach for microscopic algae species classification by implementing a compact Convolutional Neural Network (CNN) model. Our methodology was tested on a diverse dataset consisting of 18 distinct species of microscopic algae, demonstrating a remarkable classification accuracy exceeding 99%. The outstanding performance of this model is attributed to its compact architecture which maintains high precision while minimizing computational resources, making it a feasible option for real-time applications. Furthermore, we incorporated advanced data augmentation techniques to enhance the generalization capability of our model. By artificially expanding the training dataset, we effectively increased the model's robustness to variance in input data, which significantly contributed to the model's high classification accuracy. The research findings underscore the potential of compact CNN models coupled with data augmentation strategies in high-precision microscopic algae classification tasks, paving the way for future innovations in the field of aquatic microbiology and environmental monitoring.

Keywords- Customized CNN, Deep Learning, Microalgae Classification, Machine Learning, Artificial Intelligence.

I. INTRODUCTION

The task of classifying and identifying microscopic algae is crucial across a spectrum of disciplines such as environmental surveillance, biotechnology, and ecology. However, the process of manual identification can be laborious, time-intensive, and prone to errors. Thus, there has been a growing emphasis on devising automated techniques for this classification in recent times (Mittal, R., Ranade, V. 2023). Algae, a varied group of photosynthesizing microorganisms, perform a key role in aquatic ecosystems, account for 40% of global photosynthesis, and form the basis of numerous food chains.

Microalgae are increasingly being acknowledged as a renewable and sustainable bio-resource. They offer bioactive compounds that are progressively being employed across a broad array of sectors, such as food, cosmetics, pharmaceuticals, dietary supplements, agrochemicals, bio-stimulants, animal feed, and fuel (Morais Junior et al.,2020).

The traditional approach to microscopic algae classification necessitates manual identification via microscopic scrutiny, which is not only labor-intensive and time-consuming but also requires domain expertise. In contrast, advancements in machine learning, particularly techniques involving computer vision, have demonstrated potential for automating and improving the precision of microalgal classification (Chong, J. et al.2023).

Several methodologies, such as the utilization of aircraft, satellites, or drones to collect hyperspectral or multispectral images, have been adopted for tracking algal blooms, aiding the detection of such events over large-scale regions (Park J et al., 2019; Goldberg, S.J., 2016; Kudela, R.M., 2015; Lekki, J. et al., 2019). It is paramount to consistently monitor undesired algal blooms in water bodies like ponds, channels, or freshwater reservoirs to facilitate prompt and suitable responses for preserving the quality of potable water. The traditional practice of visually inspecting algal blooms under a microscope is laborious, economically unfeasible, and complex. In contrast, an automated system incorporating cutting-edge object detection algorithms presents a more effective solution for real-time surveillance of algal blooms in aquatic environments (Ali et al., 2022).

Additional research in the literature focuses on specific applications and techniques. For instance, (Piazza et al., 2021) used Convolutional Neural Network (CNN) for classifying marine coralline algae based on scanning electron microscopy (SEM) images, achieving an 80% accuracy. (Liao et al., 2022) employed the Internet of Things (IoT) approach to analyze Scenedesmus quadricauda culture. (Reimann et al., 2020) utilized fluorescent image features to distinguish between living and dead microalgae of Chlorella sp., with a classification accuracy of 95%. (Pant et al., 2020) leveraged the ResNext model for classifying seven Pediastrum species, reaching an accuracy of 98.45%. (Qian et al., 2020) implemented a Faster R-CNN-based detection method for classifying nine genera of algae, reporting a Mean Average Precision (MAP) score of 74.64%. (Sonmez et al., 2022) compared AlexNet and other architectures for the classification of two microalgae species, achieving an accuracy of 99.66%. (Gaur et al., 2022) focused

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6972
***Article Received**: 28 March 2023 **Revised**: 12 May 2023 **Accepted**: 24 May 2023*

their study on the classification of blue-green algae, attaining an accuracy of 99.16%. (Xu et al., 2022) applied a CNN architecture to classify 13 different categories of algae, with a success rate of 93%. Finally, (Luo et al., 2023) introduced a novel technique using Landsat imagery for classifying algal blooms in eutrophic shallow lakes, yielding an accuracy of 84.49%.

In recent times, deep learning-based computer vision techniques have been harnessed for problems pertaining to image classification and object detection (LeCun, Y.et al. 2015). These deep learning methodologies typically necessitate extensive datasets for training classifiers. However, procuring such large amounts of data might not always be feasible. In these scenarios, the application of transfer learning and data augmentation techniques can be beneficial, as they allow for the transfer of acquired knowledge from one task to another (West, Jeremy, 2007; George Karimpanal, 2019).

Several scholarly works have focused on evaluating individual Convolutional Neural Network (CNN) architectures or a combination of one with another. However, employing such large architectures for classifying limited class data can place a significant burden on the system's memory, increasing time complexity. Therefore, this paper introduces a Compact Convolutional Neural Network designed for microalgae classification. The goal is to aid budding researchers in creating innovative algorithms, thereby promoting research and development in the field of automated microscopic algae classification.

II. PROPOSED METHOD

Compact CNN: CNNs are a type of neural network commonly used for image recognition and processing tasks. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. In a convolutional layer, the input image is convolved with a set of learnable filters to produce a set of feature maps. The filters are small in size and slide over the input image with a certain stride, performing element-wise multiplication and summing up the results to produce a single output value in the feature map. (Good fellow et al. 2016). In this study we developed a compact CNN architecture for the micro algae classification.

We proposed a Convolutional Neural Network (CNN) architecture consisting of multiple convolutional layers followed by Batch Normalization, Dropout, and fully connected layers. The motivation behind developing a custom Convolutional Neural Network (CNN) in this study is to address the challenges of high computational cost and time complexity associated with large CNN architectures, especially when handling limited class data. The proposed Compact CNN offers an efficient and accessible solution for microalgae classification, aiming to facilitate the automation of this critical task and inspire continued innovation in this domain. Here a brief overview of the architecture is given:

- The first layer is a Conv2D layer with 16 filters, a kernel size of 3, and a ReLU activation function.
- The Batch Normalization layer normalizes the activations of the previous layer to ensure that the
- network trains faster and is less sensitive to the choice of hyper parameters.
- The second Conv2D layer also has 16 filters and a kernel size of 3, followed by another Batch Normalization layer.
- The third Conv2D layer has 16 filters and a kernel size of 5, with a stride of 2 and padding set to
  ’same’ to preserve the spatial dimensions of the input. It is followed by another Batch Normalization layer and a Dropout layer with a rate of 0.4 to prevent overfitting.
- The same pattern is repeated for the next two blocks of Conv2D layers with increasing number of filters (32 and 64) and the same kernel and stride sizes. Each block also includes Batch Normalization and Dropout layers.
- The Flatten layer converts the output of the last Conv2D layer into a 1D array.
- The first Dense layer has 128 units with a ReLU activation function and is followed by another
  Batch Normalization and Dropout layer.
- The final Dense layer has 18 units (equal to the number of classes in the output) with a softmax
  activation function to produce the final classification probabilities.

This CNN architecture is designed for classification tasks of microscopic images of algae and incorporates several techniques to improve its performance and prevent overfitting. The Mathematical formulation of the same is given below for the better understanding:

Let x be the input image, with height h, width w, and c channels.

Conv2D layer with 16 filters:

$y = \mathrm{ReLU}(\mathrm{Conv2D}(x, 16, (3, 3)))$……………………….[1]

Batch Normalization layer:

$\hat{y} = \frac{y-\mu}{\sqrt{\sigma^2+\epsilon}}$……………………………………………….[2]

where μ and σ are the mean and standard deviation of the activations across the batch, respectively, and ϵ is a small constant for numerical stability.

Conv2D layer with 16 filters:

$y = \mathrm{ReLU}(\mathrm{Conv2D}(\hat{y}, 16, (3, 3)))$…………………...[3]

Conv2D layer with 16 filters, kernel size of 5, stride of 2, and padding ’same’:

$y = \mathrm{ReLU}(\mathrm{Conv2D}(\hat{y}, 16, (5, 5)), \mathrm{strides} = (2, 2), \mathrm{padding} = '\mathrm{same}'))$ …………………………..[4]

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6972
***Article Received**: 28 March 2023 **Revised**: 12 May 2023 **Accepted**: 24 May 2023*

Layer Type	Output Shape	Kernel Size	Strides	Padding	Activation	Dropout
Conv2D	(None, 222, 222, 16)	3	-	"valid"	"relu"	-
BatchNormalization	(None, 222, 222, 16)	-	-	-	-	-
Conv2D	(None, 220, 220, 16)	3	-	"valid"	"relu"	-
BatchNormalization	(None, 220, 220, 16)	-	-	-	-	-
Conv2D	(None, 110, 110, 16)	5	2	"same"	"relu"	-
BatchNormalization	(None, 110, 110, 16)	-	-	-	-	-
Dropout	(None, 110, 110, 16)	-	-	-	-	0.4
Conv2D	(None, 108, 108, 32)	3	-	"valid"	"relu"	-
BatchNormalization	(None, 108, 108, 32)	-	-	-	-	-
Conv2D	(None, 106, 106, 32)	3	-	"valid"	"relu"	-
BatchNormalization	(None, 106, 106, 32)	-	-	-	-	-
Conv2D	(None, 53, 53, 32)	5	2	"same"	"relu"	-
BatchNormalization	(None, 53, 53, 32)	-	-	-	-	-
Dropout	(None, 53, 53, 32)	-	-	-	-	0.4
Conv2D	(None, 51, 51, 64)	3	-	"valid"	"relu"	-
BatchNormalization	(None, 51, 51, 64)	-	-	-	-	-
Conv2D	(None, 49, 49, 64)	3	-	"valid"	"relu"	-
BatchNormalization	(None, 49, 49, 64)	-	-	-	-	-
Conv2D	(None, 25, 25, 64)	5	(2, 2)	"same"	"relu"	-
BatchNormalization	(None, 25, 25, 64)	-	-	-	-	-
Dropout	(None, 25, 25, 64)	-	-	-	-	0.4
Flatten	(None, 40000)	-	-	-	-	-
Dense	(None, 128)	-	-	-	"relu"	-
BatchNormalization	(None, 128)	-	-	-	-	-
Dropout	(None, 128)	-	-	-	-	0.4
Dense	(None, 18)	-	-	-	"softmax"	-

Figure 1: The Tabular Description of our compact CNN

Figure 2. Sample Images of Microscopic Algae from our dataset

Architecture Dropout layer with a rate of 0.4: $y = \mathrm{Dropout}(y, \mathrm{rate} = 0.4)$……………………………..[5]

Two more blocks of Conv2D layers, each with 32 and 64 filters, respectively, and the same kernel and stride sizes as before, followed by Batch Normalization and Dropout layers. Note that in this notation, Conv2D(x, f, k) represents the 2D convolution operation with input x, f filters, and k kernel size while Dense(x, u) represents a fully connected layer with input x and u units. Also, ReLU and Softmax represent the Rectified Linear Unit and softmax activation functions, respectively. Details of our CNN are given in tabular form in Figure 1.

Microscopic Algae Data Set: Image Acquisition of microscopic algal images is carried out by visiting the popular fresh water bodies located in Bidar District of Karnataka state. The names of lakes are Papnash, Aurad, Narsing Jharna, Karanja Dam and Gaumukh located in the radius of 30 Km from city center. The algal samples were collected and preserved in a 5% formalin solution. Next, the samples were washed with distilled water and dissected. The dissected portions were then mounted onto glass slides using a needle and covered with a slip to observe under microscope. We used Biocraft's Trinocular Research Microscope with Eye tube angle 45 Degree 45x microscope view to capture the images of the microscopic algae. The microscope was fitted with 5.0 MP color CMOS Camera with ½ CMOS having resolution of 2592x1944 pixels and USB2.0 Interface. The selected ROI's of all images were stored in .jpg format in RGB color space for further processing. Samples are also stored in laboratory for future reference of biologist. Later on image augmentation operations were performed to enhance the dataset as advised in (Sanchez et al. 2019). Samples from our dataset are shown in Figure 2.

III. Results and Descussion

A. *Evaluation Protocol*

During the evaluation of our classification model, we employed several fundamental evaluation metrics, namely precision, recall, F-measure, and accuracy. These metrics facilitated a comprehensive assessment of the model's performance in accurately predicting the species of microalgae. Precision quantified the model's ability to provide reliable positive predictions for each category of microscopic algae, thereby minimizing false positives. In contrast, recall enabled an evaluation of the model's proficiency in avoiding false negatives and correctly identifying all positive instances associated with each microalgae type. By computing the harmonic mean of precision and recall, the F-measure provided a balanced assessment of the model's capacity to achieve both high precision and high recall simultaneously, thus offering valuable insights into its performance across multiple microalgae species. Additionally, accuracy, a commonly utilized metric, offered a holistic measure of the model's overall correctness when classifying microalgae species. Computed as the ratio of the total number of correctly predicted instances (both positive and negative) to the total number of instances in the dataset, accuracy provided an overview of the model's performance. However, we acknowledged the limitations of accuracy in dealing with imbalanced datasets. Consequently, we prioritized precision, recall, and F-measure as more informative metrics for evaluating the model's performance on a per-microalgae basis.

B. *Results and Descussion*

In this study, a compact Convolutional Neural Network (CNN) model was utilized to classify 18 different species of microscopic algae with a remarkable degree of accuracy. The performance of the model was assessed using precision, recall, and F-measure metrics, each of which provide different insights into the model's performance. The detailed classification report for the classification of microscopic algae using custom CNN is given in Table 1.

The precision for a class indicates how many of the samples predicted as that class by the model were actually of that class. A precision score of 1.00, which was achieved for 17 out of the 18 algae species, suggests an exceptionally high level of precision, with no false positives. The precision score for the Oedogonium class was slightly lower at 0.98, indicating that 98% of samples predicted as Oedogonium were correctly classified, with 2% of samples misclassified. The recall for a class shows how many of the samples of that class were correctly identified by the model. A recall score of 1.00 across all classes indicates that the model was able to identify all samples of each class correctly, which is a testament to its outstanding performance. The F-measure or F1-score is a harmonic mean of precision and recall, providing a balanced view of the two metrics. An F1-score of 1.00, as achieved for 17 out of the 18 classes, indicates perfect precision and recall. The slightly lower F1-score of 0.99 for Oedogonium and Zygnima signifies a slight imbalance between precision and recall for these classes, but still indicates an excellent performance.

The overall accuracy of the model, calculated as the proportion of all classifications that are correct, was also 1.00, indicating that the model correctly classified all samples in the test set. The weighted average of precision, recall, and F1-score, which considers the number of samples in each class, was also 1.00, reinforcing the high performance of the model across all classes. In summary, these results demonstrate that the compact CNN model, combined with data augmentation techniques, provides a highly accurate and reliable method for classifying different species of microscopic algae.

Our study further validates the superior performance of the compact CNN model through an illustrative confusion matrix and the analysis of training and validation accuracy and loss curves.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6972
***Article Received**: 28 March 2023 **Revised**: 12 May 2023 **Accepted**: 24 May 2023*

Figure 3 presents the confusion matrix which gives a detailed visual representation of the model's performance across all classes of microscopic algae. The confusion matrix reaffirms the high precision and recall rates reported earlier, with the majority of the predictions falling along the diagonal, indicating correct classifications. Off-diagonal elements, which would represent misclassifications, are notably absent or significantly minimal, further endorsing the model's accuracy.

The comparison of training and validation accuracy and loss, as depicted in Figure 4, provides critical insights into the model's learning process and its generalization ability. A close convergence of training and validation accuracy suggests that the model has learned patterns efficiently from the training data and has generalized well to unseen data, thereby avoiding overfitting. On the other hand, the loss curves provide a clear representation of the model's optimization process. A decreasing trend in both training and validation loss over epochs signifies effective learning. If the validation loss tends to increase while the training loss decreases, this would indicate overfitting; however, our model does not show this trend, which is a strong indicator of its robustness and generalization capability.

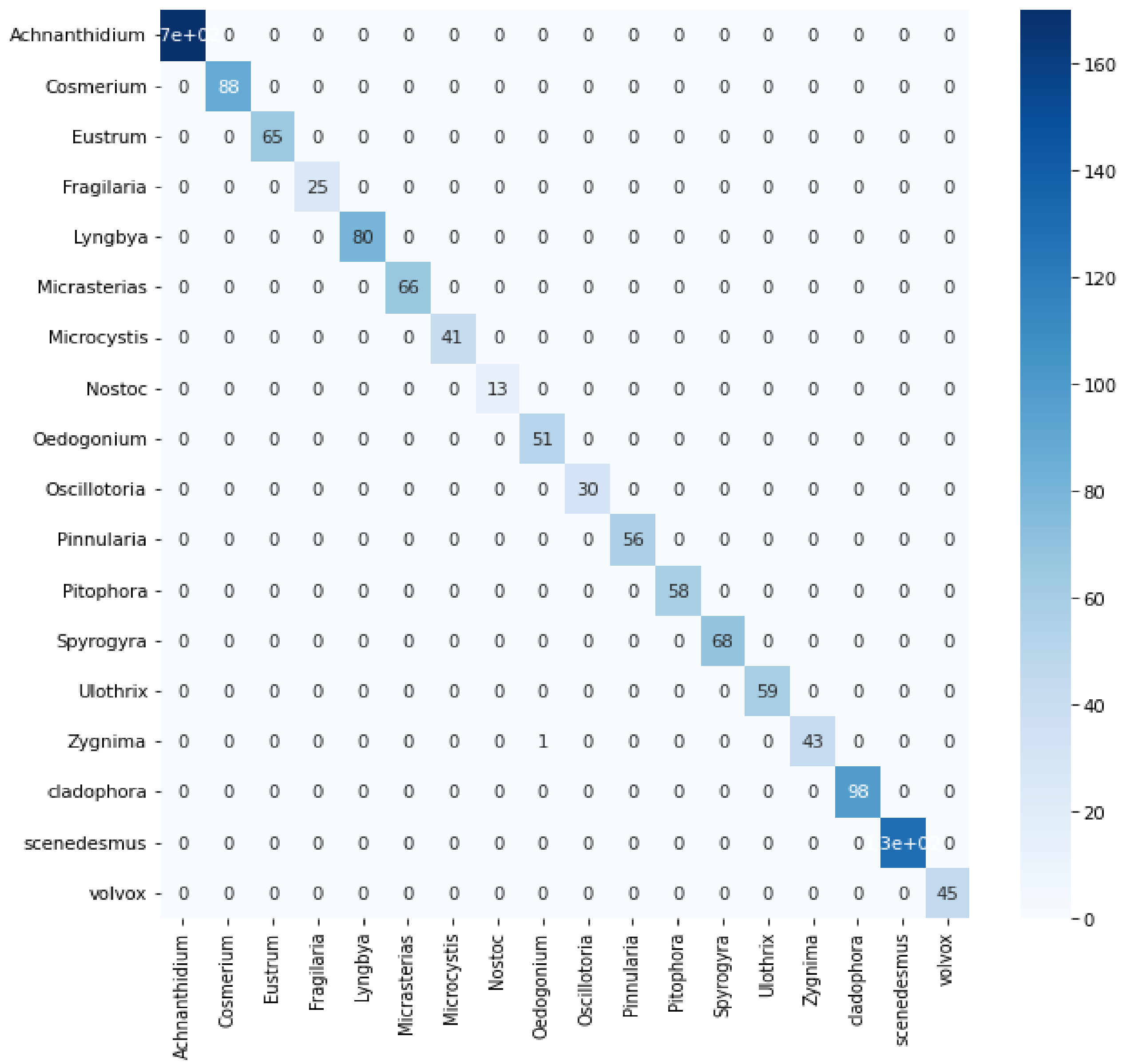

Figure 3. Confusion Matrix given Compact CNN for Microscopic Algae Classification

A comparative analysis of various methods employed for algal classification given in Table 2. reveals a range of accuracies. (Reimann et al., 2020) utilized fluorescent image features, achieving an accuracy of 95.00%, while (Pant et al., 2020) employed the RexNext Model and achieved a higher accuracy of 98.45%. (Qian et al., 2020) used Faster RCNN, which resulted in a lower accuracy of 74.64%. In 2022, both (Gaur et al. and Xu et al.) implemented a Convolutional Neural

Network (CNN), with Gaur et al. reaching an impressive accuracy of 99.16% and Xu et al. achieving an accuracy of 93.00%. Notably, the proposed method in this study employs a Compact Custom CNN, which yields the highest accuracy of all the methods at 99.91%. This comparison underscores the effectiveness of the proposed Compact Custom CNN in the classification of algae, demonstrating its potential for further development and application.

These visual and quantitative assessments accompanying of the model's performance reinforce our finding that the compact CNN model, augmented by data augmentation techniques, is an excellent tool for the task of classifying different species of microscopic algae. By effectively learning from the training data and generalizing to unseen data, the model has shown potential for real-world applications in the field of aquatic microbiology and environmental monitoring.

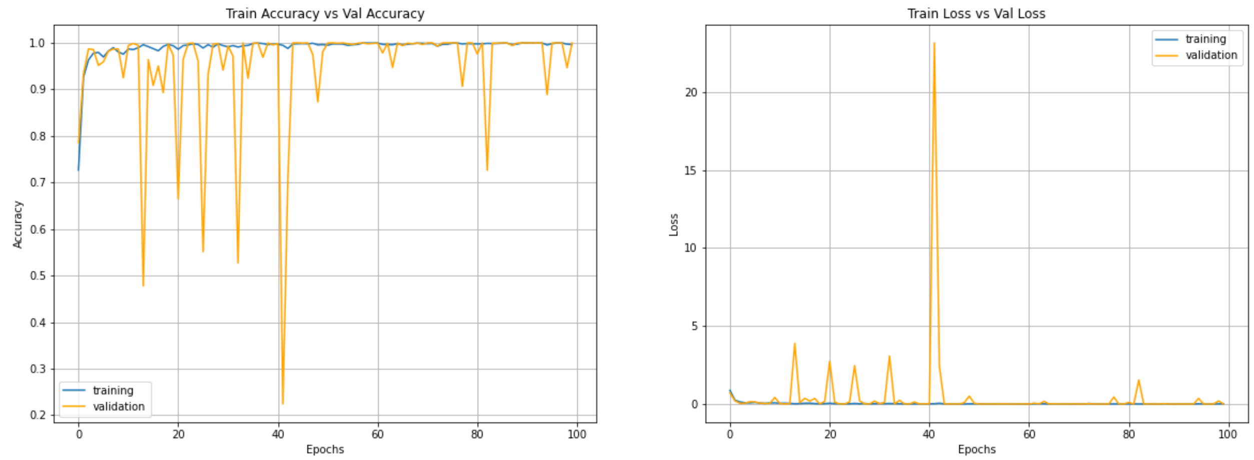

Figure 4. Graphs for Training & Validation Accuracy and Loss.

TABLE I. CLASSIFICATION REPORT OF MICROSCOPIC ALGAE BASED ON CUSTOM CNN

Sl. No.	Class of the Algae	Precision	Recall	F-measure
0	Achnanthidium	1	1	1
1	Cosmerium	1	1	1
2	Eustrum	1	1	1
3	Fragilaria	1	1	1
4	Lyngbya	1	1	1
5	Micrasterias	1	1	1
6	Microcystis	1	1	1
7	Nostoc	1	1	1
8	Oedogonium	0.98	1	0.99
9	Oscillotoria	1	1	1
10	Pinnularia	1	1	1
11	Pitophora	1	1	1
12	Spyrogyra	1	1	1
13	Ulothrix	1	1	1
14	Zygnima	1	0.98	0.99
15	Cladophora	1	1	1
16	Scenedesmus	1	1	1
17	Volvox	1	1	1

IV. CONLUSION

In this study, we proposed compact Convolutional Neural Network (CNN) model, coupled with data augmentation techniques, has demonstrated exceptional performance in classifying 18 different species of microscopic algae. The model achieved an impressive accuracy of over 99%, which was validated through various metrics such as precision, recall, and F1-score. The graphical representation of these metrics, along with the confusion matrix and the training vs. validation accuracy and loss curves, further emphasized the model's robustness, learning efficiency, and generalization capabilities. The research findings underscore the potential of machine learning, specifically compact CNN models, in high-precision microscopic algae classification tasks. This study opens up new avenues for applying such models in the field of aquatic microbiology and environmental monitoring. The successful deployment of this model could significantly enhance our understanding of algae species distribution and dynamics, and could potentially contribute to early detection systems for harmful algal blooms and other environmental anomalies.

Nevertheless, while the model's performance is highly promising, it is crucial to continue refining and validating the model with more diverse and larger datasets. Future work could also explore the integration of this model with other datasets and sources, such as environmental data, to further enhance our understanding of microscopic algae and their role in aquatic ecosystems. Overall, this study contributes significantly to the growing body of literature emphasizing the successful application of artificial intelligence techniques in biological and environmental

TABLE II. COMPARTIAVE ANALYSIS WITH PREVIOUS WORKS

Sl. No.	Year	Authors	Method	Accuracy
1	2020	Reimann et al.,	Fluorescent Image Features	95.00%
2	2020	Pant et al.	RexNext Model	98.45%
3	2020	Qian et al.,	Faster RCNN	74.64%
4	2022	Gaur et al.	CNN	99.16%
5	2022	Xu at al.	CNN	93.00%
Proposed Method			**Compact Custom CNN**	**99.91%**

REFERENCES

[1] Abdullah, Ali, S., Khan, Z., Hussain, A., Athar, A., & Kim, H. C. (2022, July 14). Computer Vision Based Deep Learning Approach for the Detection and Classification of Algae Species Using Microscopic Images. Water, 14(14), 2219. https://doi.org/10.3390/w14142219

[2] Chong, J. W. R., Khoo, K. S., Chew, K. W., Ting, H. Y., & Show, P. L. (2023, March). Trends in digital image processing of isolated microalgae by incorporating classification algorithm. Biotechnology Advances, 63, 108095. https://doi.org/10.1016/j.biotechadv.2023.108095

[3] Gaur, A., Pant, G., & Jalal, A. S. (2022, September). Computer-aided cyanobacterial harmful algae blooms (CyanoHABs) studies based on fused artificial intelligence (AI) models. Algal Research, 67, 102842. https://doi.org/10.1016/j.algal.2022.102842

[4] George Karimpanal, T., & Bouffanais, R. (2018, December 20). Self-organizing maps for storage and transfer of knowledge in reinforcement learning. Adaptive Behavior, 27(2), 111–126. https://doi.org/10.1177/1059712318818568

[5] Ms. Sweta Minj. (2012). Design and Analysis of Class-E Power Amplifier for Wired & Wireless Systems. International Journal of New Practices in Management and Engineering, 1(04), 07 - 13. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/9

[6] Heaton, J. (2017, October 29). Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning. Genetic Programming and Evolvable Machines, 19(1–2), 305–307. https://doi.org/10.1007/s10710-017-9314-z

[7] Kudela, R. M., Palacios, S. L., Austerberry, D. C., Accorsi, E. K., Guild, L. S., & Torres-Perez, J. (2015, September). Application of hyperspectral remote sensing to cyanobacterial blooms in inland waters. Remote Sensing of Environment, 167, 196–205. https://doi.org/10.1016/j.rse.2015.01.025

[8] LeCun, Y., Bengio, Y., & Hinton, G. (2015, May 27). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

[9] Liao, Y., Yu, N., Zhou, G., Wu, Y., & Wang, C. (2022, February). A wireless multi-channel low-cost lab-on-chip algae culture monitor AIoT system for algae farm. Computers and Electronics in Agriculture, 193, 106647. https://doi.org/10.1016/j.compag.2021.106647

[10] Luo, J., Ni, G., Zhang, Y., Wang, K., Shen, M., Cao, Z., Qi, T., Xiao, Q., Qiu, Y., Cai, Y., & Duan, H. (2023, March). A new technique for quantifying algal bloom, floating/emergent and submerged vegetation in eutrophic shallow lakes using Landsat imagery. Remote Sensing of Environment, 287, 113480. https://doi.org/10.1016/j.rse.2023.113480

[11] Mittal, R., & Ranade, V. (2023, April 1). Bioactives from microalgae: A review on process intensification using hydrodynamic cavitation. Journal of Applied Phycology. https://doi.org/10.1007/s10811-023-02945-w

[12] Basaligheh, P. (2021). A Novel Multi-Class Technique for Suicide Detection in Twitter Dataset. Machine Learning Applications in Engineering Education and Management, 1(2), 13–20. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/14

[13] Morais Junior, W. G., Gorgich, M., Corrêa, P. S., Martins, A. A., Mata, T. M., & Caetano, N. S. (2020, November). Microalgae for biotechnological applications: Cultivation, harvesting and biomass processing. Aquaculture, 528, 735562. https://doi.org/10.1016/j.aquaculture.2020.735562

[14] Pant, G., Yadav, D., & Gaur, A. (2020, June). ResNeXt convolution neural network topology-based deep learning model for identification and classification of Pediastrum. Algal Research, 48, 101932. https://doi.org/10.1016/j.algal.2020.101932

[15] Piazza, G., Valsecchi, C., & Sottocornola, G. (2021, December 3). Deep Learning Applied to SEM Images for Supporting Marine Coralline Algae Classification. Diversity, 13(12), 640. https://doi.org/10.3390/d13120640

[16] Stojanovic, N. . (2020). Deep Learning Technique-Based 3d Lung Image-Based Tumor Detection Using segmentation and Classification. Research Journal of Computer Systems and Engineering, 1(2), 13:19. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/6

[17] Singh, M. ., & Kumar, J. D. . (2023). WBFAS: Workflow based Failure-Aware Scheduling in Grid Computing . International Journal of Intelligent Systems and Applications in Engineering, 11(1), 208–214. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2460.

[18] Qian, P., Zhao, Z., Liu, H., Wang, Y., Peng, Y., Hu, S., Zhang, J., Deng, Y., & Zeng, Z. (2020, July). Multi-Target Deep Learning for Algal Detection and Classification. 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). https://doi.org/10.1109/embc44109.2020.9176204

[19] Reimann, R., Zeng, B., Jakopec, M., Burdukiewicz, M., Petrick, I., Schierack, P., & Rödiger, S. (2020, June). Classification of dead and living microalgae Chlorella vulgaris by bioimage informatics and machine learning. Algal Research, 48, 101908. https://doi.org/10.1016/j.algal.2020.101908

[20] Castro, J., González, J., Rodríguez, C., Garcia, J., & Jóhann, Þorvaldsson. Predicting Student Dropout Rates in Engineering Programs with Machine Learning. Kuwait Journal of Machine Learning, 1(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/105

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 7s
DOI: https://doi.org/10.17762/ijritcc.v11i7s.6972
Article Received: 28 March 2023 Revised: 12 May 2023 Accepted: 24 May 2023

[21] Sánchez, C., Vállez, N., Bueno, G., & Cristóbal, G. (2019). Diatom Classification Including Morphological Adaptations Using CNNs. Pattern Recognition and Image Analysis, 317–328. https://doi.org/10.1007/978-3-030-31332-6_28

[22] Sonmez, M. E., Eczacıoglu, N., Gumuş, N. E., Aslan, M. F., Sabanci, K., & Aşikkutlu, B. (2022, January). Convolutional neural network - Support vector machine based approach for classification of cyanobacteria and chlorophyta microalgae groups. Algal Research, 61, 102568. https://doi.org/10.1016/j.algal.2021.102568

[23] Goldberg, S.J.; Kirby, J.T.; Licht, S.C (2016). Applications of Aerial Multi-Spectral Imagery for Algal Bloom Monitoring in Rhode Island SURFO Technical Report No. 16-01. (n.d.). DigitalCommons@URI. https://digitalcommons.uri.edu/surfo_tech_reports/13

[24] Elena Petrova, Predictive Analytics for Customer Churn in Telecommunications , Machine Learning Applications Conference Proceedings, Vol 1 2021.

[25] West, J., Ventura, D. and Warnick, S. (2007) Spring Research Presentation A Theoretical Foundation for Inductive Transfer. Brigham Young University, College of Physical and Mathematical Sciences, 32. - References - Scientific Research Publishing. (n.d.). Retrieved May 16, 2023, from https://www.scirp.org/(S(i43dyn45teexjx455qlt3d2q))/reference/referencespapers.aspx?referenceid=2624976

[26] Xu, L., Xu, L., Chen, Y., Zhang, Y., & Yang, J. (2022, May 16). Accurate Classification of Algae Using Deep Convolutional Neural Network with a Small Database. ACS ES&T Water, 2(11), 1921–1928. https://doi.org/10.1021/acsestwater.1c00466.