# An Ensemble Learning Approach for Glaucoma Detection in Retinal Images

M. M. Mahdi[1*], M. A. Mohammed[2], H. Al-Chalibi[3], B. S. Bashar[4], H. A. Sadeq[5] and T. M. J. Abbas[6]

1- Anesthesia Techniques Department, Al-Mustaqbal University College, Babylon, Iraq.
Email: msc.marwah.madlool@mustaqbal-college.edu.iq (Corresponding author)
2- Department of Anesthesia Techniques, Al-Noor University College, Bartella, Iraq.
Email: mohammed.abdulkreem@alnoor.edu.iq
3- Medical Technical College, Al-Farahidi University, Baghdad, Iraq.
Email: haideralchalibi@yahoo.com
4- Al-Nisour University College, Baghdad, Iraq.
Email: bashar.s.eng@nuc.edu.iq
5- Al-Hadi University College, Baghdad,10011, Iraq.
Email: dr.haideradnan@huc.edu.iq
6- Medical device engineering, Ashur University College, Baghdad, Iraq.
Email: dr.talib@au.edu.iq

Received: 2 August 2022 Revised: 7 September 2022 Accepted: 14 October 2022

**ABSTRACT:**
To stop vision loss from glaucoma, early identification and regular screening are crucial. Convolutional neural networks (CNN) have been effectively used in recent years to diagnose glaucoma automatically from color fundus pictures. CNNs can extract distinctive characteristics directly from the fundus pictures, as opposed to the current automatic screening techniques. In this study, a CNN-based deep learning architecture is created for the categorization of normal and glaucomatous fundus pictures. In this paper, we propose a deep learning-based framework for the detection of glaucoma based on retinal images. Our proposed approach utilizes the two CNN-based models, namely Inception and DenseNet, in order to classify the input images. We also show the impact of transfer learning on the training and the validation processes and put forward an effective pipeline with lower trainable parameters for the target task. Our experiments on a collected dataset demonstrate the efficacy of the proposed model by achieving an accuracy of 93.84%, a precision of 92.83%, and a recall of 95.00%.

**KEYWORDS:** Glaucoma Detection, Convolutional Neural Networks, Medical Images Analysis, Retinal Images, DenseNet, Inception.

## 1. INTRODUCTION

A chronic eye condition known as glaucoma is brought on by optic nerve damage brought on by high intraocular pressure [1]. Glaucoma is predicted to impact over 80 million individuals worldwide by the year 2020 [2]. There are no indications of visual loss in the early stages of glaucoma, but when it worsens over time, it may result in irreversible blindness [3]. Another sign of glaucoma, in addition to visual loss, high intraocular pressure, and damage to the optic nerve, is a significant cup-to-disc ratio [4]. Even though there is no cure, early therapy can slow the decline of vision.

In the clinical setting, glaucoma is diagnosed by intraocular pressure monitoring, visual-field testing, or optic disk inspection on fundus imaging [5]. Even though intraocular pressure is a sign of glaucoma, measuring it is not a reliable technique to detect the disease since some glaucoma patients may have normal eye pressure [6]. Contrarily, visual-field testing necessitates specialized tools that certain clinics might not have. The last technique, optic disk examination, is more practical than the first two and is utilized by experts for early glaucoma identification more frequently [7]. It still has the drawbacks of being expensive and time-consuming.

The fact that glaucoma affects millions of individuals worldwide prompted researchers to look into the automated diagnosis of glaucoma [8]. Researchers have tried to employ deep Convolutional Neural Networks (CNNs) for glaucoma detection since they were first



Paper type: Research paper
DOI: 10.30486/mjee.2022.696522
How to cite this paper: M. M. Mahdi, M. A. Mohammed, H. Al-Chalibi, B. S. Bashar, H. A. Sadeq and T. M. J. Abbas, "An Ensemble Learning Approach for Glaucoma Detection in Retinal Images", Majlesi Journal of Electrical Engineering, Vol. 16, No. 4, pp. 117-122, 2022.

introduced. Their study largely concentrated on two topics. In the first, deep learning was used for feature extraction, while in the second, domain expertise and medical characteristics were used for detection [9].

Following the remarkable performance of CNN-based models in various fields [10]-[11]-[12]-[13], they have been utilized in several recent research to categorize glaucoma [14]. In one of them, Ahn et al. [15] used a GoogleNet Inception model and a newly developed CNN model to explore the effectiveness of early and advanced glaucoma diagnosis of fundus pictures. On two fundus datasets, Chen et al. [16] employed deep learning, dropout, and data augmentation approaches to identify glaucoma. In [17], fundus pictures' features were extracted using CNN, and an SVM classifier was used to divide the images into normal and glaucomatous kinds. By fusing the deep hierarchical context of a collection of fundus pictures with the local optic disc area, Fu et al. [18] suggested a disc-aware ensemble network for automated glaucoma screening. The performance of a deep learning approach to identify referable glaucomatous optic neuropathy on fundus pictures was demonstrated by Li et al. [19]. A few deep learning architectures and fundus photos of patients of different racial and ethnic backgrounds were utilized in [20] to identify glaucomatous optic neuropathy. In order to detect glaucoma using fundus pictures, Shibata et al. [21] built a deep learning system and compared the outcomes to three ophthalmologists.

In this paper, we propose an ensemble learning approach that utilizes deep neural networks, specifically two CNN-based models, named Inception and DenseNet, to detect glaucoma from the retinal images. The proposed approach, also, uses transfer learning to optimize the training procedure. Further, a novel dataset, collected in an Iraqi hospital, is introduced for training and evaluation. Overall, our contributions in this paper are as follows:

1. A novel ensemble learning approach is put forward which is capable of detecting glaucoma from the retinal images.
2. Transfer learning is utilized for optimizing the training process and making it more efficient.
3. A novel dataset collected in an authentic healthcare center is introduced.

The rest of the paper is outlined as the following. In section 2, the proposed approach is detailed. Section 3 includes our experimental setup and results. Finally, section 4 draws the conclusion.

## 2. MATERIALS AND METHODS

### 2.1. Overview

In this section, we include the details of our proposed approach. Fig. 1 illustrates an overview of all the steps existent in our algorithm. As is observed in Fig .1, after a preprocessing step, the input images are fed to a feature extraction module containing two CNN-based models. Then, the feature maps are fused together in order to be fed into a fully connected block for being classified into classes of normal and glaucomatous.

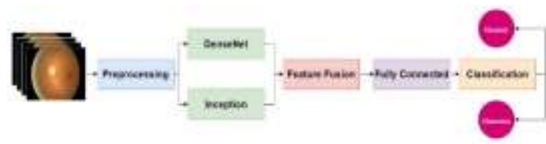


**Fig. 1.** An overview of the proposed framework.

### 2.2. Dataset

All images were taken with the patient's permission at the Bazzaz Iraqi hospital in Iraq. Clinical investigators chose patients with galucoma based on their examination's clinical results. Ages of the chosen patients ranged from 20 to 90, with a fairly equal proportion of men and women. The normal class was selected from patients who were undergoing standard refraction testing and did not have glaucoma. With the eyes dilated, all pictures were captured using the following data collection protocol: OD-centered, 30-degree Field-of-View, 2734 1900 pixel size, JPG uncompressed image format. Other than this, there were no other imaging restrictions placed on the acquisition procedure. To measure inter-observer variation in marking, ground truth was gathered for each picture from four glaucoma specialists with experience ranging from 2, 4, and 30 years, respectively. Low contrast, the placement of the OD area, and other factors indicating poor quality were disregarded. The fundus area (picture region with retinal features) was isolated from the original image in this dataset release by removing the surrounding non-fundus black zone, yielding an image with a resolution of around 2132 1470 pixels. Fig. 2 illustrates samples from both classes in the collected dataset.


**Fig. 2.** The samples from both classes in the dataset.

### 2.3. Preprocessing

In our proposed methodology, the images undergo two preprocessing steps. Firstly, they are reshaped to have a dimension of favored size and then they are normalized. The process of normalization is frequently used to prepare data for machine learning [22]. The purpose of normalization is to convert the values of the dataset's numeric columns to a standard scale without losing information or distorting the ranges of values. Some algorithms need normalization in order to properly model the data. Assume, for instance, that your input dataset has two columns, one with values from 0 to 1, and the other with values from 10,000 to 100,000. When attempting to integrate the values as features during modeling, issues might arise due to the significant disparity in size between the numbers. By generating new values that preserve the broad distribution and ratios in the original data while maintaining values within a scale that is applied across all numeric columns utilized in the model, normalization avoids these issues [23].

## 2.4. Data Augmentation

In data analysis, there are methods for increasing the amount of data by adding copies of previously existing data that have been significantly changed or by generating new synthetic data from existing data [24]. When a machine learning model is being trained, it serves as a regularizer and aids in lowering overfitting. In data analysis, it is strongly connected to oversampling [25]. Particularly for biological data, which tend to be high dimensional and sparse, synthetic data augmentation is of utmost relevance for machine learning classification.

## 2.5. Inception

CNNs employ inception modules to reduce dimension using stacked 11 convolutions, enabling more effective computation and deeper networks. The modules were created to address a variety of problems, including overfitting and computational cost [26]. In essence, the idea is to use various kernel filter sizes within the CNNs and arrange them to work at the same level rather than stacking them sequentially. CNNs utilize Inception Modules to cut down on processing costs. A neural network must be properly built since it processes a huge variety of pictures with widely varying conspicuous sections, sometimes referred to as the highlighted image content [27]. An input is convolutioned using not one, but three separate size filters in the most condensed form of an inception module (1x1, 3x3, 5x5). Max pooling is also used. The outputs are then concatenated and forwarded to the following layer. The CNN is set up such that all of its convolutions are performed at the same level, which causes the network to grow in width rather than depth [28]. The neural network may be configured to add an extra 1x1 convolution before the 3x3 and 5x5 layers to further reduce the computational cost of the operation. This limits the number of input channels and makes 1x1 convolutions significantly less expensive than 5x5 convolutions [29]. However, it is crucial to remember that the 1x1 convolution is inserted after the max-pooling layer and not beforehand. The GoogLeNet or Inception v1 design of this first Inception Module is well-known. The inception module has undergone additional modifications to address problems like the vanishing gradient problem.

## 2.6. DenseNet

DenseNet [30] is a more advanced architecture of CNN for visual object identification that uses fewer parameters to provide state-of-the-art performance. DenseNet and ResNet are quite similar, with a few key differences. While ResNet [31] utilizes an additive attribute to mix the output of the preceding layer with the output of the subsequent layers, DenseNet employs concatenated attributes to do the same [32]. By closely tying together all of the levels, the DenseNet Architecture seeks to solve this issue. DenseNets concatenate rather than sum the layer output functionality maps and the inputs. A simple communication model for enhancing information flow across layers is provided by DenseNet: The characteristics of all preceding layers provide input to the layer before that. The architecture of DenseNet is shown in Fig. 3.

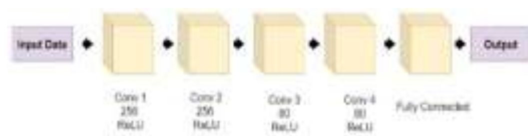


**Fig. 3.** A Confusion Matrix (CM) that is used for evaluating classifiers.

## 2.7. Transfer Learning

A model created for one task is used as the basis for another using the machine learning technique known as transfer learning [33]. Given the enormous computing and time resources needed to develop neural network models on these problems and from the enormous leaps in a skill that they provide on related problems, it is a common approach in deep learning to use pre-trained models as the starting point for computer vision and natural language processing tasks. Transfer learning is frequently used to solve challenges in predictive modeling that take input from images.

# 3. EXPERIMENTAL RESULTS

## 3.1. Experimental Setup

All of the implementation methods for the suggested technique are listed in this subsection. Programming was done with Python 3.9, while the deep learning framework was done with Pytorch 1.3. The computer we utilized for training has a GeForce RTX 1060 graphics processor and a Core i7, 3.8 GHz, central processing unit (CPU). Additionally, the autoencoder training batch size is 64, and the learning rate is 0.003 per batch. Adam is the optimizer that was used to implement the model, which has been trained for 55 epochs.

### 3.2. Evaluation Criteria

In this subsection, we explain all the metrics used for evaluating our proposed approach. Firstly, Fig. 4 demonstrates a Confusion Matrix (CM), which contains four elements, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These elements are elaborated in Table 3. Further, the metrics are demonstrated in Table 4.

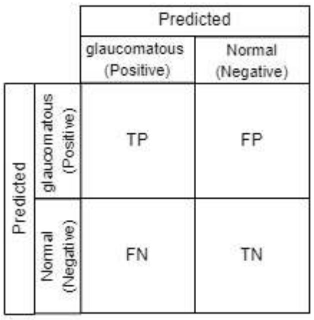


**Fig. 4.** A Confusion Matrix (CM) that is used for evaluating classifiers.

**Table. 3.** CM's elements definition.

| Metric | Definition |
|---|---|
| TP | Positive samples that are correctly classified as positive |
| TN | Negative samples that are correctly classified as negative |
| FP | Negative samples that are incorrectly classified as positive |
| FN | Positive samples that are incorrectly classified as negative |

**Table. 4.** The metrics used for evaluating our proposed method.

| Metric | Calculation |
|---|---|
| Accuracy | $\frac{TP+TN}{TP+FP+FN+TN}$ |
| Precision | $\frac{TP}{TP+FP}$ |
| Recall | $\frac{TP}{TP+FN}$ |
| F1-Score | $\frac{2\times Precision\ \times Recall}{Precision+Recall}$ |

### 3.3. Classification Performance

The results obtained by the suggested classifier using the metrics provided in section 3.2 are included in this part. The CM and the outcomes of our suggested approach are described in detail in Fig. 5 and Table 5.

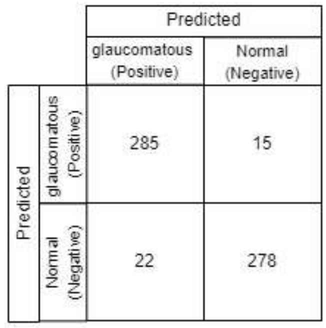


**Fig. 5.** Obtained CM.

**Table. 5.** Results achieved by the proposed framework.

| Metric | Accuracy (%) | Recall (%) | Precision (%) | F1-Score (%) |
|---|---|---|---|---|
| Obtained Value | 93.84 | 92.83 | 95.00 | 93.90 |

Moreover, Fig. 6 illustrates the accuracy vs. epoch curve for training the model. Fig. 7 demonstrates the loss vs. epoch.

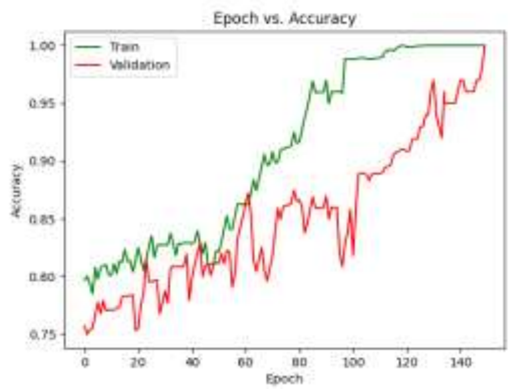


**Fig. 6.** Training and validation accuracy vs. epoch curve.

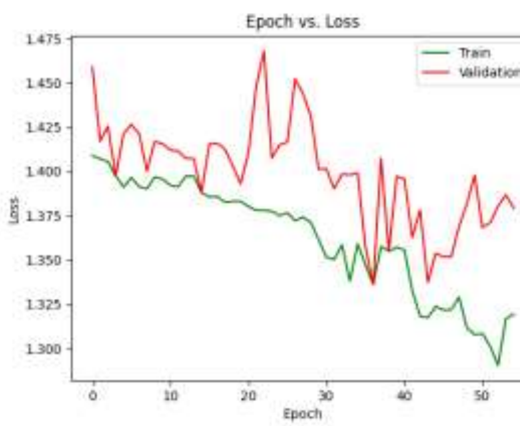


**Fig. 7.** Training and validation loss vs. epoch curve.

Furthermore, Table 6 details a comparison between our proposed methodology and other state-of-the-art research works. This comparison is done using the accuracy achieved by each methodology.

**Table. 6.** Comparison between our proposed method and other state-of-the-art works.

| Research | Accuracy (%) |
|---|---|
| [34] | 90.00 |
| [35] | 85.00 |
| [36] | 96.97 |
| [37] | 93.32 |
| Our proposed method | 93.84 |

Based on Table 6, our suggested methodology's accuracy results are quite competitive with those of the previous works. This demonstrates the algorithm's dependability in categorizing retinal pictures. Furthermore, we can assert that the model has considerable performance in identifying both TP and TN samples within the dataset utilized in this study based on the F1-Score that is attained by our suggested technique.

## 4. CONCLUSION

In this paper, we offer a deep learning-based framework for detecting glaucoma in retinal images. Using two deep learning models, namely Inception and DenseNet, fundus images are classified as having glaucoma or being normal. Extensive experiments demonstrate that in terms of accuracy, recall, precision, and the F1-Score, the proposed methodology has a remarkable performance. Thus, our approach can be utilized in clinical contexts with reliable and trustworthy results.

## REFERENCES


[1] Ran, An Ran, Clement C. Tham, Poemen P. Chan, Ching-Yu Cheng, Yih-Chung Tham, Tyler Hyungtaek Rim, and Carol Y. Cheung. **"Deep learning in glaucoma with optical coherence tomography: a review."** *Eye* 35, No. 1, pp. 188-201, 2021.

[2] Thompson, Atalie C., Alessandro A. Jammal, and Felipe A. Medeiros. **"A review of deep learning for screening, diagnosis, and detection of glaucoma progression."** *Translational Vision Science & Technology* 9, No. 2, pp. 42-42, 2020.

[3] Mirzania, Delaram, Atalie C. Thompson, and Kelly W. Muir. **"Applications of deep learning in detection of glaucoma: a systematic review."** *European Journal of Ophthalmology* 31, No. 4, pp. 1618-1642,2021.

[4] Asaoka, Ryo, Hiroshi Murata, Kazunori Hirasawa, Yuri Fujino, Masato Matsuura, Atsuya Miki, Takashi Kanamoto et al. **"Using deep learning and transfer learning to accurately diagnose early-onset glaucoma from macular optical coherence tomography images."** *American journal of ophthalmology* 198, pp. 136-145, 2019.

[5] Serte, Sertan, and Ali Serener. **"A generalized deep learning model for glaucoma detection."** In *2019 3rd International symposium on multidisciplinary studies and innovative technologies (ISMSIT)*, pp. 1-5. IEEE, 2019.

[6] Sreng, Syna, Noppadol Maneerat, Kazuhiko Hamamoto, and Khin Yadanar Win. **"Deep learning for optic disc segmentation and glaucoma diagnosis on retinal images."** *Applied Sciences* 10, No. 14, pp. 4916, 2020.

[7] Lee J, Kim YK, Park KH, Jeoung JW. **"Diagnosing glaucoma with spectral-domain optical coherence tomography using deep learning classifier."** *Journal of glaucoma*. 29(4),pp. 287-94, 2020.

[8] Veena, H. N., A. Muruganandham, and T. Senthil Kumaran. **"A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images."** *Journal of King Saud University-Computer and Information Sciences* (2021).

[9] Asaoka, Ryo, Masaki Tanito, Naoto Shibata, Keita Mitsuhashi, Kenichi Nakahara, Yuri Fujino, Masato Matsuura, Hiroshi Murata, Kana Tokumo, and Yoshiaki Kiuchi. **"Validation of a deep learning model to screen for glaucoma using images from different fundus cameras and data augmentation."** *Ophthalmology Glaucoma* 2, No. 4, pp. 224-231, 2019.

[10] Sharghi, Elnaz, Vahid Nourani, Hessam Najafi, and Amir Molajou. **"Emotional ANN (EANN) and wavelet-ANN (WANN) approaches for Markovian and seasonal based modeling of rainfall-runoff process."** *Water resources management* 32, No. 10, pp. 3441-3456, 2018.

[11] Nourani, Vahid, Zahra Razzaghzadeh, Aida Hosseini Baghanam, and Amir Molajou. **"ANN-based statistical downscaling of climatic parameters using decision tree predictor screening method."** *Theoretical and Applied Climatology* 137, No. 3, pp. 1729-1746, 2019.

[12] Ali, Waqar, Wenhong Tian, Salah Ud Din, Desire Iradukunda, and Abdullah Aman Khan. **"Classical and modern face recognition approaches: a complete review."** *Multimedia Tools and Applications* 80, No. 3, pp. 4825-4880, 2021.

[13] Chen, Chun-Fu Richard, Quanfu Fan, and Rameswar Panda. **"Crossvit: Cross-attention multi-scale vision transformer for image classification."** In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 357-366. 2021.

[14] Zafar, Afia, Muhammad Aamir, Nazri Mohd Nawi, Sikandar Ali, Mujtaba Husnain, and Ali Samad. **"A Comprehensive Convolutional Neural Network Survey to Detect Glaucoma Disease."** *Mobile Information Systems* 2022, 2022.

[15] Deperlioglu, Omer, Utku Kose, Deepak Gupta, Ashish Khanna, Fabio Giampaolo, and Giancarlo Fortino. **"Explainable framework for Glaucoma diagnosis by image processing and convolutional neural network synergy: analysis with doctor evaluation."** *Future Generation Computer Systems* 129, pp. 152-169, 2022.

[16] Babu, Ch, G. Prabaharan, and R. Pitchai. **"Efficient detection of glaucoma using double tier deep**

**convolutional neural network."** *Personal and Ubiquitous Computing* (2022), pp. 1-11, 2022.

[17] RUI, CHIARA, Silvia Gazzina, Giovanni Montesano, David P. Crabb, David F. Garway-Heath, Francesco Oddone, Paolo Lanzetta et al. **"Convolutional Neural Network for Glaucoma detection using Compass color fundus images."** *Investigative Ophthalmology & Visual Science* 63, no. 7 (2022): 2039-A0480.

[18] Liu, Yuan, Leonard Wei Leon Yip, Yuanjin Zheng, and Lipo Wang. **"Glaucoma screening using an attention-guided stereo ensemble network."** *Methods* 202 (2022), pp. 14-21.

[19] Gupta, Ravi Kumar, Utkarsh Sharma, and Vivek Singh. **"Detection of Glaucoma using Deep Learning."** *International Journal of Research in Engineering, Science and Management* 5, No. 5, pp. 147-150, 2022.

[20] Akbar, Shahzad, Syed Ale Hassan, Ayesha Shoukat, Jaber Alyami, and Saeed Ali Bahaj. **"Detection of microscopic glaucoma through fundus images using deep transfer learning approach."** *Microscopy Research and Technique* 85, No. 6, pp. 2259-2276, 2022.

[21] Garg, H., Gupta, N., Agrawal, R., Shivani, S. and Sharma, B., 2022. **"A real time cloud-based framework for glaucoma screening using EfficientNet."** *Multimedia Tools and Applications*, pp.1-22.

[22] Kumar, S., Gupta, S. and Arora, S., 2022. **"A comparative simulation of normalization methods for machine learning-based intrusion detection systems using KDD Cup'99 dataset."** *Journal of Intelligent & Fuzzy Systems*, (Preprint), pp.1-18.

[23] Izonin, Ivan, Roman Tkachenko, Nataliya Shakhovska, Bohdan Ilchyshyn, and Krishna Kant Singh. **"A Two-Step Data Normalization Approach for Improving Classification Accuracy in the Medical Diagnosis Domain."** *Mathematics* 10, No. 11 (2022): 1942.

[24] Yang, Haitao, Jiali Li, Kai Zhuo Lim, Chuanji Pan, Tien Van Truong, Qian Wang, Kerui Li et al. **"Automatic strain sensor design via active learning and data augmentation for soft machines."** *Nature Machine Intelligence* 4, No. 1, pp. 84-94, 2022.

[25] Temraz, Mohammed, and Mark T. Keane. **"Solving the class imbalance problem using a counterfactual method for data augmentation."** *Machine Learning with Applications* (2022): 100375.

[26] Khouloud, S., Ahlem, M., Fadel, T. and Amel, S., **"W-net and inception residual network for skin lesion segmentation and classification."** *Applied Intelligence*, *52*(4), 2022, pp.3976-3994.

[27] Pawar, Kamlesh, Zhaolin Chen, N. Jon Shah, and Gary F. Egan. **"Suppressing motion artefacts in MRI using an Inception- ResNet network with motion simulation augmentation."** *NMR in Biomedicine* 35, no. 4 (2022): e4225.

[28] Mujahid, Muhammad, Furqan Rustam, Roberto Álvarez, Juan Luis Vidal Mazón, Isabel de la Torre Díez, and Imran Ashraf. **"Pneumonia Classification from X-ray Images with Inception-V3 and Convolutional Neural Network."** *Diagnostics* 12, No. 5 (2022): 1280.

[29] Bhat, Sachin S., Alaka Ananth, Rajashree Nambiar, and Nagaraj Bhat. **"Building Dataset and Deep Learning-Based Inception Model for the Character Classification of Tigalari Script."** In *Recent Advances in Artificial Intelligence and Data Engineering*, pp. 239-252. Springer, Singapore, 2022.

[30] Vakharia, Vinay, Jay Vora, Sakshum Khanna, Rakesh Chaudhari, Milind Shah, Danil Yu Pimenov, Khaled Giasin, Parth Prajapati, and Szymon Wojciechowski. **"Experimental investigations and prediction of WEDMed surface of Nitinol SMA using SinGAN and DenseNet deep learning model."** *journal of materials research and technology* 18 (2022), pp. 325-337.

[31] Bohmrah, Maneet Kaur, and Harjot Kaur. **"Classification of Covid-19 patients using efficient fine-tuned deep learning DenseNet model."** *Global Transitions Proceedings* 2, No. 2 (2021), pp. 476-483.

[32] Lu, Tao, Baokun Han, Lipin Chen, Fanqianhui Yu, and Changhu Xue. **"A generic intelligent tomato classification system for practical applications using DenseNet-201 with transfer learning."** *Scientific Reports* 11, No. 1, pp. 1-8, 2021.

[33] Kim, Yongtae, Youngsoo Kim, Charles Yang, Kundo Park, Grace X. Gu, and Seunghwa Ryu. **"Deep learning framework for material design space exploration using active transfer learning and data augmentation."** *Computational Materials* 7, No. 1, pp. 1-7, 2021.