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Human Skin Disease Detection Using Machine Learning

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Abstract: In this research, I want to improve deep convolution neural networks that have been successful with the ImageNet dataset at categorizing seven different types of skin lesions using the HAM10000 dataset, which has 10,000 dermatoscopic pictures. With VGG16, Inception V3, Inception ResNet V2, and Dense Net 201, the top layers were fine-tuned.

I. INTRODUCTION

The several processing layers are used in the deep learning approach to teach data representation in hierarchies. With just a few people working on it, it provides a method to harness a lot of data. Beginning with the development of AlexNet in 2012, the Deep Learning approach has made tremendous strides and evolution in computer vision in recent years.Identifying differences between photographs of various entities is a fairly generic skill that may be used to a variety of challenges.

Since the very final layers of the network learn the semantics and high-level features, Deep CNN has the unique property that its initial levels often learn highly generic and "low-level" properties of pictures.

The following are the project's works:

1) Fine-tune DCNNs for 10000 dermoscopic images of 7 different types of skin lesions.
2) Inception V3, Dense Net 201, is used to fine-tune all of the layers.
3) Evaluate the performance of the following DCNNs: Dense Net 201, Inception ResNet V2, and VGG16. Every DCNN is adjusted from the top layers down.
4) Construct a seamless ensemble of Inception V3 and Dense Net 201.

II. PROBLEM STATEMENT

The purpose of our system is to make predictions for the general and more commonly occurring disorder that when unchecked can become fatal diseases. The system applies data mining techniques, does pre-processing on the data and then implements the Deep Learning algorithms.

This system will forecast the prospective ailment based on the symptoms provided and the preventative steps needed to prevent the condition from getting worse. It will also help doctors study the trends of currently prevalent diseases.

III. RESEARCH OBJECTIVE

The goal of this project is to forecast diseases in advance in order to save lives, lower treatment costs, and prevent diseases from developing in the first place.

The non-manual medical method, which is excellent for enhancing and comprehending human health, should be adopted in India as well.

The major goal is to improve patient care by applying the theory of machine learning to the healthcare industry.

Various diseases may now be identified and predicted considerably more easily because to machine learning. Numerous machine learning algorithms are used in predictive disease analysis, which aids in both disease prediction and patient treatment.

IV. RESEARCH CHALLENGE

Infrastructure Requirements for Testing & Experimentation

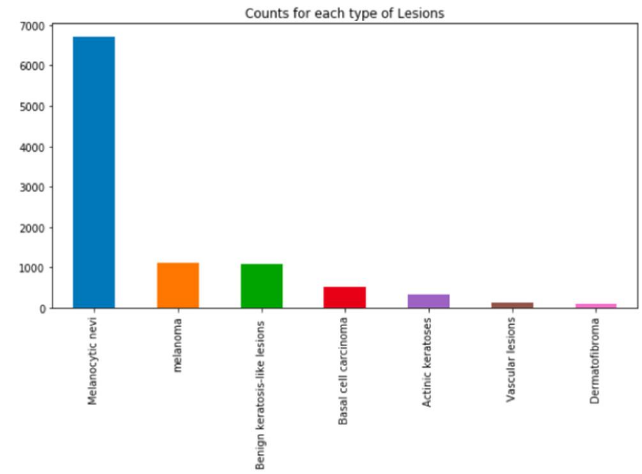
1) Time-Consuming Implementation
2) Affordability
3) Clutter in the Background
4) Requires large dataset

V. LITERATURE SURVEY

S.No	Paper Title	Summary	Algorithms Used	Pros / Cons
[1]	Acharya, U. R., Fujita, H., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Application of deep convolutionalneural network for automated detection of myocardial infarction using ECG signals.Information Sciences 415–416, 190–198. https://doi.org/10.1016/j.ins.2017.06.027	This study proposed diagnosing MI using 11 deep CNNs layers automatically, using two separate databases (noise and without noise).	CNN	Pros: 1. Learning Capabilities 2. Massive Data Capacity 3. Picture Perfect Cons: 1. Slower Operation 2. Improper Translations 3. Long Training Period
[2]	Ahmed, S., Choi, K. Y., Lee, J. J., Kim, B. C., Kwon, G. R., Lee, K. H., & Jung, H. Y. (2019). Ensembles of Patch-Based Classifiers for Diagnosis of Alzheimer Diseases. IEEE Access, 7, 73373–73383. https://doi.org/10.1109/ACCESS.2019.2920011	The study's objective is to increase the degree of accuracy comparable to state-of-the-art techniques, address the problem of overfitting, and examine validated brain technologies that include noticeable AD diagnostic features.	CNN	Pros: 1. Learning Capabilities 2. Massive Data Capacity 3. Picture Perfect Cons: 1. Slower Operation 2. Improper Translations 3. Long Training Period
[3]	Naqi, S. M., Sharif, M., & Jaffar, A. (2020). Lung nodule detection and classification based on geometric fit in parametric form and deep learning. Neural Computing and Applications, 32(9), 4629–4647. https://doi.org/10.1007/s00521-018-3773-x	Because the system's problem includes false-positive results, this work provides an automated detection system and classification to promote radiologists' diagnosis.	Deep Learning	Pros: Effective at Producing High-Quality Results The Cost-Effectiveness Scalability Cons: Massive Data Requirement High Processing Power Struggles With Real-Life Data
[4]	Rustam, F., Reshi, A. A., Mehmood, A., Ullah, S., On, B. W., Aslam, W., & Choi, G. S. (2020). COVID-19 Future Forecasting Using Supervised Machine Learning Models. IEEE Access, 8, 101489–101499. https://doi.org/10.1109/ACCESS.2020.2997311	The purpose of this research Provides displays the potential of ML models to estimate the number of future patients affected by COVID-19, which is widely regarded as a possible danger to humanity.	Linear Regression	Pros: Simple model Computationally efficient Interpretability of the Output Cons: Linearity Assumption Severely affected by Outliers Independence of variables
[5]	Liu, J., Xu, H., Chen, Q., Zhang, T., Sheng, W., Huang, Q., Song, J., Huang, D., Lan, L., Li, Y., Chen, W., & Yang, Y. (2019). Prediction of hematoma expansion in spontaneous intracerebral hemorrhage using support vector machine. EBioMedicine, 43, 454–459. https://doi.org/10.1016/j.ebiom.2019.04.040	The expanding of hematoma is in anticipation that spontaneously ICH derives from accessible comparable by the usage of SVM	Support Vector Machine	Pros: more effective in high dimensional spaces. relatively memory efficient. Cons: not suitable for large data sets. required training time is higher.
[6]	Javeed, A., Zhou, S., Yongjian, L., Qasim, I., Noor, A., & Nour, R. (2019). An Intelligent Learning System Based on Random Search Algorithm and Optimized Random Forest Model for Improved Heart Disease Detection. IEEE Access, 7, 180235–180243. https://doi.org/10.1109/ACCESS.2019.2952107	Develop an intelligent system that would show good performance on both training and testing data diagnosis of heart failure.	Random Forest	Pros: Robust to outliers. Works well with non-linear data. Cons: Random forests are found to be biased while dealing with categorical variables. Slow Training.
[7]	Acharya, U. R., Fujita, H., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. Information Sciences, 415–416, 190–198. https://doi.org/10.1016/j.ins.2017.06.027	This study proposed diagnosing MI using 11 deep CNNs layers automatically, using two separate databases (noise and without noise).	CNN	Pros: 1. Learning Capabilities 2. Massive Data Capacity 3. Picture Perfect Cons: 1. Slower Operation 2. Improper Translations 3. Long Training Period
[8]	Kousarrizi, M. R. N., Seiti, F., & Teshnehlab, M. (2012). An Experimental Comparative Study on Thyroid Disease Diagnosis Based on Feature Subset Selection and classification. International Journal of Electrical & Computer	Choose the best methods of feature selection and classification for thyroid disease diagnosis, which is one of the most critical classification problems	Support Vector Machine	Pros: more effective in high dimensional spaces. relatively memory efficient. Cons: not suitable for large data sets. required training time is higher.
[9]	Cinarer, G., & Emiroglu, B. G. (2019). Classificatin of Brain Tumors by Machine Learning Algorithms. 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies, ISMSIT 2019 - Proceedings. https://doi.org/10.1109/ISMSIT.2019.8932878	training automatically and ultimately make a wise decision with high accuracy.	Support Vector Machines	Pros: more effective in high dimensional spaces. relatively memory efficient. Cons: not suitable for large data sets. required training time is higher.
[10]	Senturk, Z. K., & Kara, R. (2014). Breast Cancer Diagnosis Via Data Mining: Performance Analysis of Seven Different Algorithms. Computer Science & Engineering: An International Journal, 4(1), 35–46. https://doi.org/10.5121/cseij.2014.4104	Determine the best approaches to lead to early breast cancer detection. An overview of the diagnosis of breast cancer in patients is given.	KNN	Pros: No Training Period Easy Implementation Cons: Feature Scaling Does not work well with large dataset

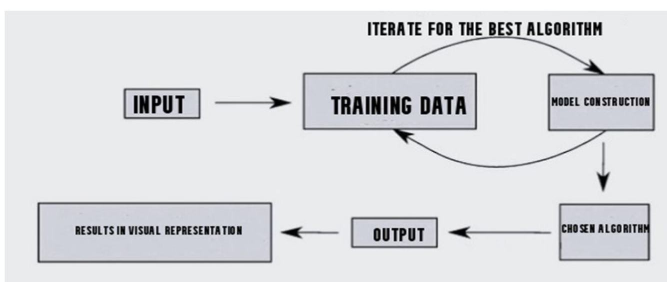
VI. PROPOSED SYSTEM

The data are explored and made ready for neural network training.The dataset contains seven skin lesions: melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. The majority of skin lesions are benign, with the exception of melanoma, which is exceedingly dangerous, and basal cell carcinoma and actinic keratoses, both of which can be cancerous. The dataset contains 8000 benign samples and 2000 malignant cases. Melanocytic nevi, which include about 7000 cases, are also overrepresented in the sample. Therefore, our neural network model should achieve accuracy of more than 60% even in the worst-case situation.



The original photos are 450 × 600 pixels in size, which is far too large. I thus scale the images to 64 x 64 RGB images for the baseline model and 192 x 256 pixels for fine-tuning models.

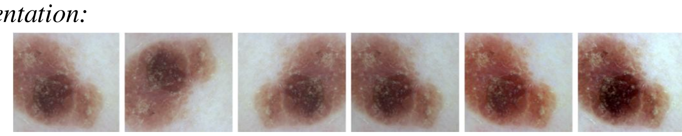
Divided into 7210 training examples, 1803 validation examples, and 1002 test examples, the dataset has been normalized by dividing by 255.



Baseline Model: I develop a tiny CNN to gauge how tough it will be to classify skin lesions before fine-tuning DCNNs.VGG16: Despite the fact that many DCNNs models perform better on ImageNet than VGG16.VGG16 was fine-tuned.Inception:The Inception modules, which are essentially little versions of the larger model, are what give the third version of Inception its name. The idea that you must choose what kind of convolution you want to make at each layer.Densenet:Dense Net, a newly released DCNN architecture, ranks among the best on ImageNet with a top-1 ranking of 0.936 and a top-5 ranking of 0.773. Although Dense Net performs similarly to Inception V3 in terms of performance.

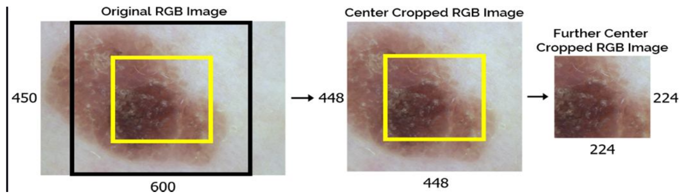
VII. IMPLEMENTATIONAND OUTPUT

1) *Train/Test-Time Data Augmentation:*



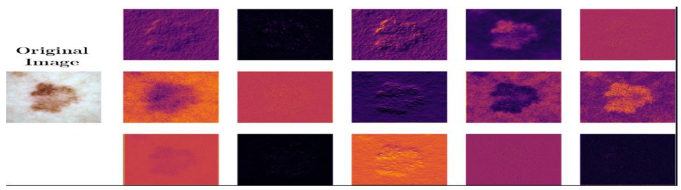
1.vertical 2.horizontal 3. flips, brightness shift 4.saturation 5.contrast 6.boost used at train-time to broaden the In order to provide a complete forecast from the classifier that is unaffected by the orientation or illumination circumstances of the scan, data representation beyond constrained pre-existing samples, and test-time are required.Predictions from all 6 variations [including the original 1] are averaged to obtain the final prediction per sample.

2) *Multi Scale Input:*



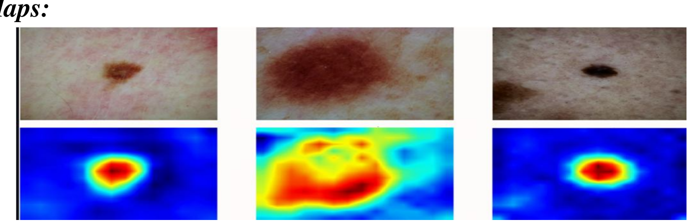
Original RGB image (left), center cropped 448 x 448 x 3 image used to train 3 CNN member models and the A 224 × 224 x 3 picture that has been centre cropped further was utilised to train 2 additional CNN member models. According to the theory that the collective ensemble benefits from a multi-scale input, each model learns to categorise at a separate scale.

3) *Feature Maps:*



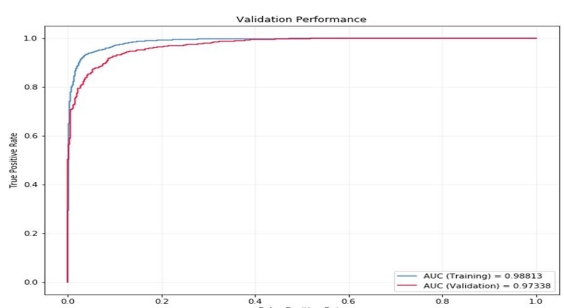
Features maps produced by the second block of expanded convolutional layers in a previously trained Once the network has processed an input image of a skin lesion using Efficient Net-B6, ImageNet weights.

4) ***Gradient Class Activation Maps:***

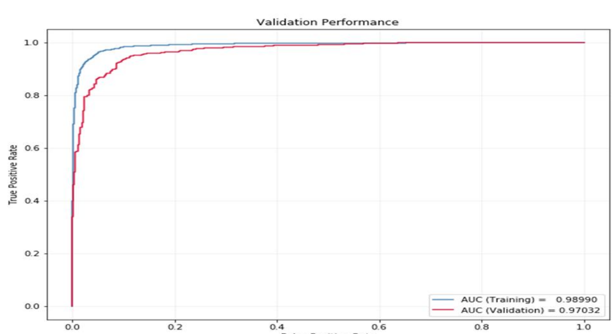


Gradient-Class Activation Maps (Grad-CAM) from adjusted Efficient Net-B6 - using the nevus class gradients flowing into the final convolutional layer - create a coarse localization map emphasizing key areas in the image for nevus prediction.

5) *Efficient Net-B6:*



6) *Inception-V3:*



VIII. RESULTS AND DISCUSSIONS

Fine-tuning the top layers:

Model	Validation	Test	Test Loss	Depth	# Params
Baseline Model	77.48%	76.54%	0.646671	11 layers	2,124,839
VGG16	79.82%	79.64%	0.708	23 layers	14,980,935
Inception V3	79.935%	79.94%	0.7482	315 layers	22,855,463
Inception ResNet V2	80.82%	82.53%	0.6691	784 layers	55,127,271
DenseNet 201	**85.8%**	**83.9%**	0.691	711 layers	19,309,127

Fine-tuning all layers

Model	Validation	Test	Test Loss
Inception V3	86.92%	86.826%	0.6241
DenseNet 201	86.696%	87.725%	0.5587
Ensemble (Inception V3 and DenseNet 201)	**88.8%**	**88.52%**	**0.41156**

The outcomes of fine-tuning all layers are superior to those of fine-tuning simply the top layers, and it takes less time to do so as well. This is due to the fact that I only performed for 20 epochs when fine-tuning all layers, whereas I perform for 30 epochs when fine-tuning the top layers.The results wouldn't be as good if I merely fine-tuned the top layers for a few epochs. According to this finding, fine-tuning the entire model leads to better final results and speeds up convergence of the model compared to just the top layers.Dense Net 201 provides the best single outcome in both scenarios, which is amazing considering that this model has even less parameters than Inception V3. thick Net is a very thick, deep model with few parameters, as stated in [5]. The effectiveness of DenseNet 201 in this experiment confirms the validity of employing DenseNet 201 for transfer learning on a dataset from a totally new domain that was pre trained on ImageNet. I used ensemble learning to generate an ensemble of the previously fully-tuned Inception V3 and DenseNet 201 models,and I got the best results with 88.8% accuracy on the validation set and 88.52% accuracy on the test set.

IX. CONCLUSION

By using the techniques of transfer learning and ensemble learning, I was able to assemble a fine-tuned version of Inception V3 with DenseNet 201 that produced accuracy for HAM10000 of 88.52% on the test set and 88.8% on the validation set. Through testing, I've discovered that fine-tuning the entire model for this dataset not only produces better results overall but also hastens the model's convergence.

Overfitting is one severe issue that has been noted throughout training. All of my experiments have a 10–13% overfit to the training set. There are numerous techniques to reduce overfitting, but I was unable to reduce it any further.The models will improve when future efforts are made to avoid overfitting and develop better training strategies.

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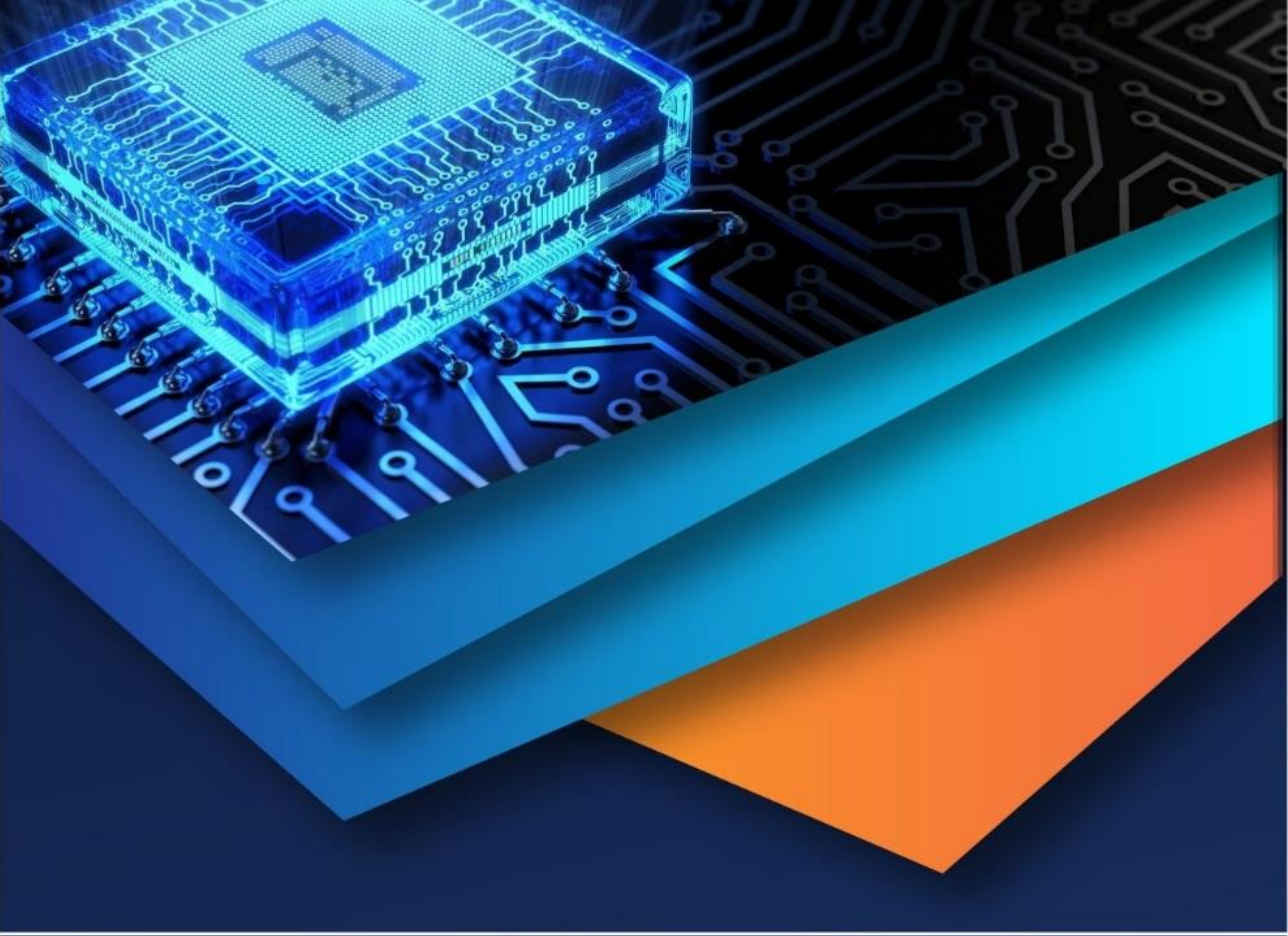

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