INVESTIGATION ON DOWN SYNDROME DETECTION AND CLASSIFICATION USING RESNET34 IN COMPARISON WITH RESNET18 FOR BETTER CLASSIFICATION ACCURACY

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ABSTRACT

Aim: The aim of the project is to improve the classification accuracy in down syndrome detection using ResNet34 in comparison with ResNet18 classifiers. **Materials and Methods:** The dataset of the ResNet34 and ResNet18 is taken from Kaggle open access data. A total of 20 samples are collected from a dataset from Kaggle. Total 20 samples are used for two groups and 10 samples are used ResNet34 (group-1) and it is compared with ResNet18 (group-2). The total samples were calculated using sample computation with pretest power of 80 % where Alpha is 0.05 and Beta is 0.2. **Result:** From MATLAB simulation, ResNet34 achieved an accuracy rate of 87.4 % compared to accuracy rate of 82.5 % by ResNet18. The statistical analysis was calculated and done by performing an independent variable t t-test with significance value of 0.002 ($p<0.05$). **Conclusion:** It is concluded that the entropy, energy, contrast and brightness feature extraction show higher accuracy of the ResNet34 algorithm compared to the ResNet18 algorithm from the considered dataset.

Keywords: ResNet34, ResNet18, Novel Down syndrome detection, Deep learning, Fetus Image, Classifier, Neural Network.

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1. Introduction

Down syndrome detection is a condition identified with mental health that affects how an individual sees and associates with others, messing up social connection and correspondence. The confusion likewise incorporates constrained and monotonous examples of conduct (V. Kumar et al., 2020). The expression "Spectrum" in the novel down syndrome detection issue alludes to the wide scope of indications and seriousness. Novel down syndrome detection incorporates conditions that were recently viewed as an independent spectrum, Asperger's disorder, youth disintegrative issue and an undefined type of inescapable developmental disorder (Stewart, 2007). Novel down syndrome detection starts in early youth and in the end, causes issues working in the public eye socially, in school and at work, for instance. Regularly kids show indications of mental imbalance inside the primary year (V. Kumar et al., 2020; Parasu et al., 2020).

Many research articles were published on down syndrome detection in the past 5 years. 59 articles were published in IEEE xplore and 38 articles were published in Science Direct. This paper reviews the work on several imaging modalities and a strategy published for the identification of Down syndrome, as well as presents the application of deep learning techniques in determining the existence of Down syndrome (Zammit et al., 2021). This paper provides an overview of the many states of deep learning techniques used with neural network classifiers available for detecting down syndrome, as well as a comparison analysis of each approach (Vincy Devi V.K & Rajesh R, 2016). (Rondal et al., 1999) used various diagnostics methods from karyotyping to rapido molecular methods and non-invasive diagnosis. This article considers the epidemiology, genetics, associated risks, antenatal screening and potential ethico-legal issues relating to the disorder before discussing clinical features, complications and monitoring requirements done by using neural network classifiers (Pan et al., 2018). Down disorder additionally raises the probability of obtaining Alzheimer's illness. Different issues. Other wellbeing worries that might be associated with down condition incorporate endocrine issues, dental issues, seizures, ear diseases, and hearing and vision debilitations (Ankith et al., 2021).

Our institution is keen on working on latest research trends and has extensive knowledge and research experience which resulted in quality publications (Dinesh Kumar et al., 2022; J. A. Kumar et al., 2022; Mahesh et al., 2022; Mohanavel et al., 2022; Ram et al., 2022; Rinesh et al., 2022; Sathish et al., 2022; Sudhan et al., 2022; Sundararaman et al., 2022; Vijayalakshmi et al., 2022; Yaashikaa et al., 2022). In the existing papers they have used many deep learning techniques for the detection of down syndrome. The accuracy of predicting down syndrome is very less accurate for overcoming this, they are using machine learning and deep learning techniques for an accurate detection of the several relatable problems. They have used different types of diagnostics techniques for down syndrome detection for getting better accuracy because general clinical methods are having less accuracy. In this research the study is done on the algorithms of Residual Neural Network (ResNet) classifiers to identify the novel down syndrome detection.

2. Materials and Methods:

This work is carried out in the Department of Electronics and Communication Engineering at Saveetha Institute of Medical and Technical Sciences, Chennai. Two groups of low resolution and different illuminated fetus images are created, each dataset consists of 10 samples, in total 20 samples with threshold 0.05, 95 % confidence and pretest power 80 % is taken for testing (Catalano et al., 2020). In this paper on the novel down syndrome detection, there are two groups. In sample preparation group 1 sample is 10 and the performance analysis is done by using ResNet34 and group 2 sample is 10 and the performance analysis is done by using ResNet18 and the total sample size is 20 the analysis is done by using MATLAB simulation platform. This project was done using MATLAB simulation. The entire experiment was carried out on a Windows platform with a dual core processor, a resolution of 1024x768 pixels, an Intel i5 CPU, 8GB of RAM, a 500GB hard drive, and MATLAB 2014 software with the necessary add-ons for training and testing processes.

This methodology involves two kinds of samples to test and train the algorithm i.e., healthy and down syndrome. The testing process starts with the data collection which is done from the kaggle dataset followed by the preprocessing stage. It refers to the transformation of the raw data before it is fed to the deep learning algorithms. It includes the conversion of RGB image into grayscale image.

Segmentation of an image is a method in which a digital image is broken into various subgroups. It helps in reducing the complexity of

the image. It is used for calculating the pixel size of the image. Here Region growing opening and Region growing ending process are taking place. Region growing is a sequential technique for image segmentation by assembling pixels into large regions based on predefined seed pixels. Edge Detection is used to identify the digital images for discontinuities, sharp changes in the image brightness. It identifies the edges of the facial features like eyes, nose, mouth.

Feature extraction is a type of dimensionality reduction where a large number of pixels of the image are efficiently represented in such a way that interesting parts of the image are captured. The features extracted here are entropy, energy, brightness and contrast. The model can be built for testing and training the data using ResNet34 and ResNet18 classifiers. At the end of the testing the down syndrome disease can be classified as sick, if no down syndrome disease can be classified as healthy.

Statistical Analysis

Statistical analysis is done using an independent sample test in SPSS software (Larson-Hall & Mizumoto, 2019). Using this statistical tool group statistics provides mean, std. deviation and std.mean error. Further using an independent sample t-test the accuracy analysis of two groups were compared for the significance values. For the independent variables the input data set and epoch values are used and for the dependent variables the accuracy values are used in novel down syndrome detection.

3. Results

In this study, it was discovered that ResNet34 appeared to have higher accuracy than ResNet18 for the identification of down syndrome detection. From Table 1, the average calculation of 20 images of novel down syndrome detection images are analyzed using ResNet34 and ResNet18 classification approach and it is observed ResNet34 performs better accuracy of 87.4 % than the ResNet18 classifier with accuracy of 82.51 %.

From Table 2, the statistical analysis of ResNet34 & ResNet18 classifiers, the ResNet34 is having a high mean of 87.4 and ResNet18 with the low mean value of 82.51 and the standard deviation of 3.027 for ResNet34 and 3.049 for ResNet18.

From Table 3, the output of group statistics independent samples T-test have got a significance of 0.002 which is less than the level of standard significance range. Hence it is proved that method X and Y are significantly different from each other.Then the bar graph is plotted representing relationship between the groups and accuracy with error bar indication.

In Fig. 1, shows the preprocessing stage where the RGB image is converted into grayscale. The original image is converted into grayscale image for better accuracy. A total of 9 images were taken during the preprocessing stage. Fig. 1. (a), (b), (d), (f), (g) are normal child images. Fig. 1.(c), (e), (h), (i) are down syndrome child images. In Fig. 2, the Segmentation process is done and the pixel size of each and every image is calculated. The initial pixel size of every image is shown in the segmentation process. Here spatial fuzzy c means clustering is used for image segmentation. Here the digital image is broken into various subgroups. It helps in reducing the complexity of the image.

Figure 3, shows the accuracy differences of the training dataset between ResNet34 and ResNet18 techniques. It shows the output of the image obtained in the MATLAB simulation tool. In region growing,opening the initial position of with 241.1799 as initial pixel value. In the region growing ending process it is found 20726 pixels within the threshold range (761 polygon vertices).

Figure 4, shows the performance of Resnet34 has attained greater accuracy of mean 87.4 % with the error rate of 0.922 and ResNet18 has accuracy 82.51 % with error rate 0.964. X Axis: ResNet34 vs ResNet18 and Y Axis: mean accuracy with error bars of 95 % CI and $\pm$ 1 SD.

4. Discussion

In this study the independent sample test is done with the significance value of 0.002 ($P<0.05$). ResNet34 has a better accuracy of (87.43±3.027) compared to ResNet18 classifier accuracy of (82.5±3.049). The standard error mean of ResNet34 is 0.922 and the standard error mean of ResNet18 is 0.964.

Down syndrome also increases the risk of developing Leukemia disease. The other health issues that may be associated with novel down syndrome detection are heart defects, sleep apnea and obesity (Pan et al., 2018). The thermal images which contain fetus images will have more noise and that noise can be removed by filtering the fetus image (Hou et al., 2019). Down's syndrome causes a distinct facial appearance, intellectual disability and developmental delays. It may be associated with thyroid or heart disease (Bee & Vidhya, 2020). There are nearly one baby in every 1000

born in the UK has the condition. Parents are often frightened and confused by the birth of a baby with Down syndrome, and they need reassurance as well as up-to-date information regarding the condition (Selikowitz, 2008).

The accuracy of Residual Neural Network classifiers is determined by the quality of the fetus image and the quality of the data, with large data and prediction data, the prediction data will be slow, and it is sensitive to the scale of data and irrelevant data, which requires a large amount of memory to store all of the information. The future work of this method is to minimize noise by filtering the fetus image more precisely and minimizing time complexity.

5. Conclusion

In this down syndrome detection, a comparative analysis of performance and evaluation of ResNet34 and ResNet18 are trained out using RGB black and white fetus images. The results of these experiments prove that ResNet34 (87.43 %) has better accuracy compared with the ResNet18 (82.51 %).

Declaration

Conflict of interests

No conflict of interest in this manuscript.

Author Contributions

Author PB was involved in data collection, data analysis and manuscript writing. Author MB was involved in conceptualization, data validation, and critical review of manuscript.

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6. Reference

Ankith, P. S., Sai Ankith, P., & Mariam Bee, M. K. (2021). EEG Processing for Computer-Aided Seizure Detection Using Artificial Neural Networks. In Emerging Technologies in Data Mining and Information Security (pp. 963–971). https://doi.org/10.1007/978-981-15-9774-9_88

Bee, M. K. M., & Vidhya, K. (2020). An automated methodology for the classification of focal and nonfocal EEG signals using a hybrid classification approach. In International Journal of Imaging Systems and Technology (Vol. 30, Issue 1, pp. 147–153). https://doi.org/10.1002/ima.22360

Catalano, G., Robeel, R. A., Cheney, G. A., Spurling, B. C., Catalano, M. C., Schultz, S. K., & Sanchez, D. L. (2020). Antidepressant Augmentation: A Review of the Literature and a Review of the Pharmacoeconomic Considerations. Journal of Clinical Psychopharmacology, 40(4), 396–400.

Dinesh Kumar, M., Godvin Sharmila, V., Kumar, G., Park, J.-H., Al-Qaradawi, S. Y., & Rajesh Banu, J. (2022). Surfactant induced microwave disintegration for enhanced biohydrogen production from macroalgae biomass: Thermodynamics and energetics. Bioresource Technology, 350, 126904.

Hou, Y., Ma, Z., Liu, C., & Loy, C. C. (2019). Learning Lightweight Lane Detection CNNs by Self Attention Distillation. In 2019 IEEE/CVF International Conference on Computer Vision (ICCV). https://doi.org/10.1109/iccv.2019.00110

Kumar, J. A., Aravind Kumar, J., Sathish, S., Krithiga, T., Praveenkumar, T. R., Lokesh, S., Prabu, D., Annam Renita, A., Prakash, P., & Rajasimman, M. (2022). A comprehensive review on bio-hydrogen production from brewery industrial wastewater and its treatment methodologies. In Fuel (Vol. 319, p. 123594). https://doi.org/10.1016/j.fuel.2022.123594

Kumar, V., Arora, H., Harsh, & Sisodia, J. (2020). ResNet-based approach for Detection and Classification of Plant Leaf Diseases. In 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC). https://doi.org/10.1109/icesc48915.2020.9155585

Larson-Hall, J., & Mizumoto, A. (2019). Using statistical analysis software (R, SPSS). In The Routledge Handbook of Research Methods in Applied Linguistics (pp. 385–397). https://doi.org/10.4324/9780367824471-33

Mahesh, N., Balakumar, S., Danya, U., Shyamalagowri, S., Babu, P. S., Aravind, J., Kamaraj, M., & Govarthanan, M. (2022). A review on mitigation of emerging contaminants in an aqueous environment using microbial bio-machines as sustainable tools: Progress and limitations. In Journal of Water Process Engineering (Vol. 47, p. 102712). https://doi.org/10.1016/j.jwpe.2022.102712

Mohanavel, V., Kumar, K. R., Sathish, T., Velmurugan, P., Karthick, A., Ravichandran, M., Alfarraj, S., Almoallim, H. S., Sureshkumar, S., & JoshuaRamesh Lalvani, J. I. (2022). Investigation on Inorganic Salts K2TiF6 and KBF4 to Develop Nanoparticles Based TiB2 Reinforcement Aluminium Composites. Bioinorganic Chemistry and Applications, 2022, 8559402.

Pan, X., Hu, X., Zhang, Y. H., Feng, K., Wang, S. P., Chen, L., Huang, T., & Cai, Y. D. (2018). Identifying Patients with Atrioventricular Septal Defect in Down Syndrome Populations by Using Self-Normalizing Neural Networks and Feature Selection. Genes, 9(4). https://doi.org/10.3390/genes9040208

Parasu, P., Epps, J., Sriskandaraja, K., & Suthokumar, G. (2020). Investigating Light-ResNet Architecture for Spoofing Detection Under Mismatched Conditions. In Interspeech 2020. https://doi.org/10.21437/interspeech.2020-2039

Ram, G. D., Dinesh Ram, G., Praveen Kumar, S., Yuvaraj, T., Babu, T. S., & Balasubramanian, K. (2022). Simulation and investigation of MEMS bilayer solar energy harvester for smart wireless sensor applications. In Sustainable Energy Technologies and Assessments (Vol. 52, p. 102102). https://doi.org/10.1016/j.seta.2022.102102

Rinesh, S., Maheswari, K., Arthi, B., Sherubha, P., Vijay, A., Sridhar, S., Rajendran, T., & Waji, Y. A. (2022). Investigations on Brain Tumor Classification Using Hybrid Machine Learning Algorithms. Journal of Healthcare Engineering, 2022, 2761847.

Rondal, J.-A., Perera, J., & Nadek, L. (1999). Down Syndrome: A Review of Current Knowledge. Wiley.

Sathish, T., Mohanavel, V., Arunkumar, M., Rajan, K., Soudagar, M. E. M., Mujtaba, M. A., Salmen, S. H., Al Obaid, S., Fayaz, H., & Sivakumar, S. (2022). Utilization of Azadirachta indica biodiesel, ethanol and diesel blends for diesel engine applications with engine emission profile. In Fuel (Vol. 319, p. 123798). https://doi.org/10.1016/j.fuel.2022.123798

Selikowitz, M. (2008). Down Syndrome. Oxford University Press, USA.

Stewart, K. (2007). Helping a Child with Nonverbal Learning Disorder Or Asperger's Disorder: A Parent's Guide. New Harbinger Publications.

Sudhan, M. B., Sinthuja, M., Pravinth Raja, S., Amutharaj, J., Charlyn Pushpa Latha, G., Sheeba Rachel, S., Anitha, T., Rajendran, T., & Waji, Y. A. (2022). Segmentation and Classification of Glaucoma Using U-Net with Deep Learning Model. Journal of Healthcare Engineering, 2022, 1601354.

Sundararaman, S., Aravind Kumar, J., Deivasigamani, P., & Devarajan, Y. (2022). Emerging pharma residue contaminants: Occurrence, monitoring, risk and fate assessment – A challenge to water resource management. In Science of The Total Environment (Vol. 825, p. 153897). https://doi.org/10.1016/j.scitotenv.2022.153897

Vijayalakshmi, V. J., Arumugam, P., Ananthi Christy, A., & Brindha, R. (2022). Simultaneous allocation of EV charging stations and renewable energy sources: An Elite RERNN-m2MPA approach. In International Journal of Energy Research (Vol. 46, Issue 7, pp. 9020–9040). https://doi.org/10.1002/er.7780

Vincy Devi V.K, & Rajesh R. (2016, March). A study on Down syndrome detection based on Artificial Neural Network in Ultra sonogram images. 2016 International Conference on Data Mining and Advanced Computing (SAPIENCE). 2016 International Conference on Data Mining and Advanced Computing (SAPIENCE), Ernakulam, India. https://doi.org/10.1109/sapience.2016.7684172

Yaashikaa, P. R., Kumar, P. S., Jeevanantham, S., & Saravanan, R. (2022). A review on bioremediation approach for heavy metal detoxification and accumulation in plants. Environmental Pollution , 301, 119035.

Zammit, M. D., Tudorascu, D. L., Laymon, C. M., Hartley, S. L., Zaman, S. H., Ances, B. M., Johnson, S. C., Stone, C. K., Mathis, C. A., Klunk, W. E., Cohen, A. D., Handen, B. L., & Christian, B. T. (2021). PET measurement of longitudinal amyloid load identifies the earliest stages of amyloid-beta accumulation during Alzheimer's disease progression in Down syndrome. NeuroImage, 228, 117728.

Preethi, P. S., Hariharan, N. M., Vickram, S., Manian, R., Manikandan, S., Subbaiya, R., ...

& Awasthi, M. K. (2022). Advances in bioremediation of emerging contaminants from industrial wastewater by oxidoreductase enzymes. Bioresource Technology, 127444.

Tables & Figures

Table 1. The accuracy obtained for 20 images where mean accuracy rate is 87.43 % for ResNet34 classifier and 82.51 % for ResNet18 algorithm.

S.No.	ResNet34	ResNet18
1	91.6	87.13
2	89.7	84.80
3	87.1	82.20
4	90.2	85.90
5	84.3	83.80
6	85.9	80.31
7	88.4	79.40
8	86.9	81.80
9	83.2	78.23
10	82.1	86.51

Table 2. The statistical analysis of mean, standard deviation and standard error rate for ResNet34 and ResNet18. It is observed that ResNet34 gives better accuracy compared to ResNet18. The mean value for ResNet34 is 87.43 and for ResNet18 is 82.513. The standard deviation value for ResNet34 is 3.027 and for ResNet18 is 3.049. The standard error mean for ResNet34 is 0.9228 and for ResNet18 is 0.9642.

	Group	**N**	**Mean**	**Std.Deviation**	**Std.Error Mean**
Accuracy	ResNet34	10	87.4300	3.02765	.92280
	ResNet18	10	82.5130	3.04932	.96428

Table 3. Independent sample T-test for ResNet34 and ResNet18. In the t-test, the observed significance value is 0.002 ($p<0.005$). There is a significant difference in the accuracy of the down syndrome detection.

	Levene's Test for Equality of Variances		**t-test for Equality of Means**	**95% Confidence Interval of the Difference**

		F	Sig	t	df	Sig (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Accuracy	Equal Variances assumed	0.016	.900	3.684	18	.002	4.91700	1.33469	2.11292	7.72108
	Equal Variances not assumed			3.684	17.955	.002	4.91700	1.33469	2.11263	7.72147

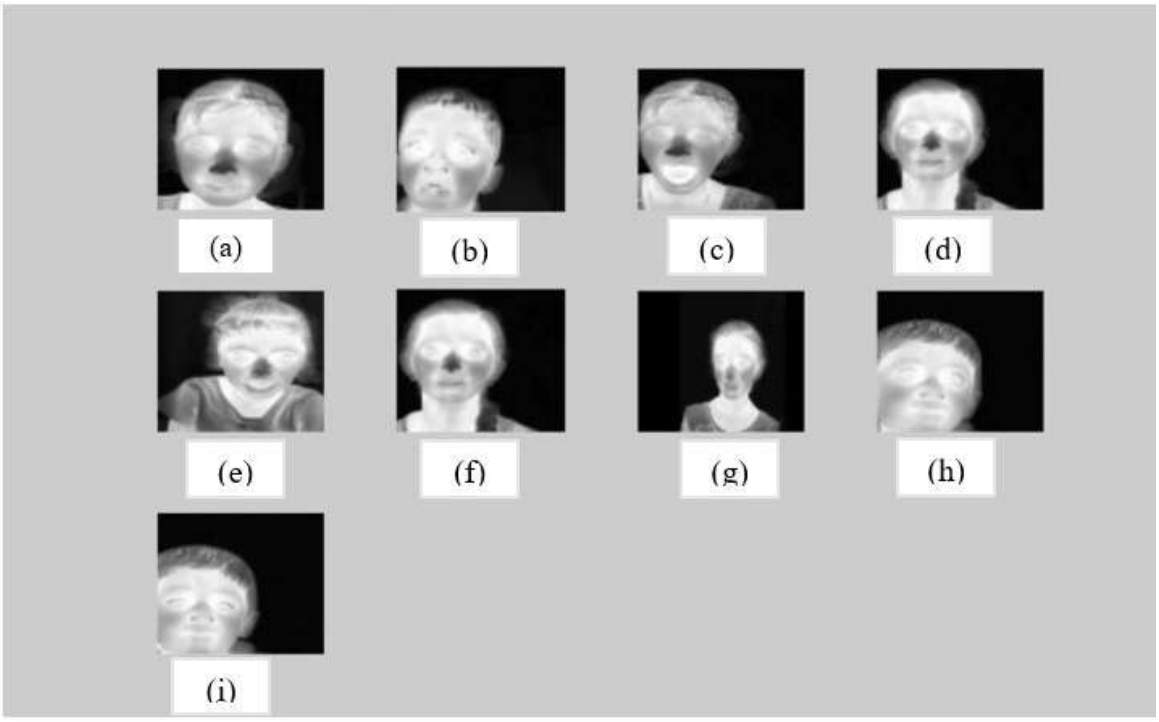

Fig. 1**.** The preprocessing stage for Down Syndrome Detection. Here the RGB image is converted into grayscale image. A total of 9 images were taken during the preprocessing stage. Fig. (a), (b), (d),(f), (g) are normal child images. Fig. (c), (e), (h), (i) are down syndrome child images.

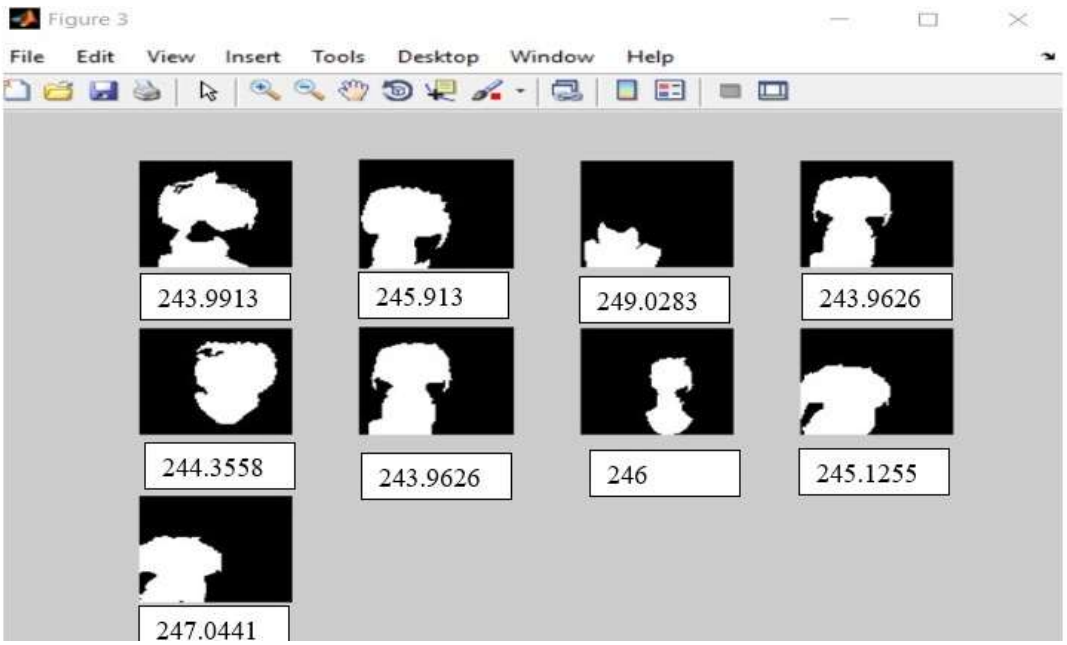

Fig. 2**.** The Segmentation process. Here the pixel size of each and every image is verified and in the case of eyes, nose and mouth, full facial features are verified. Here the region is iteratively grown by comparing the all unallocated neighboring pixels to the image.

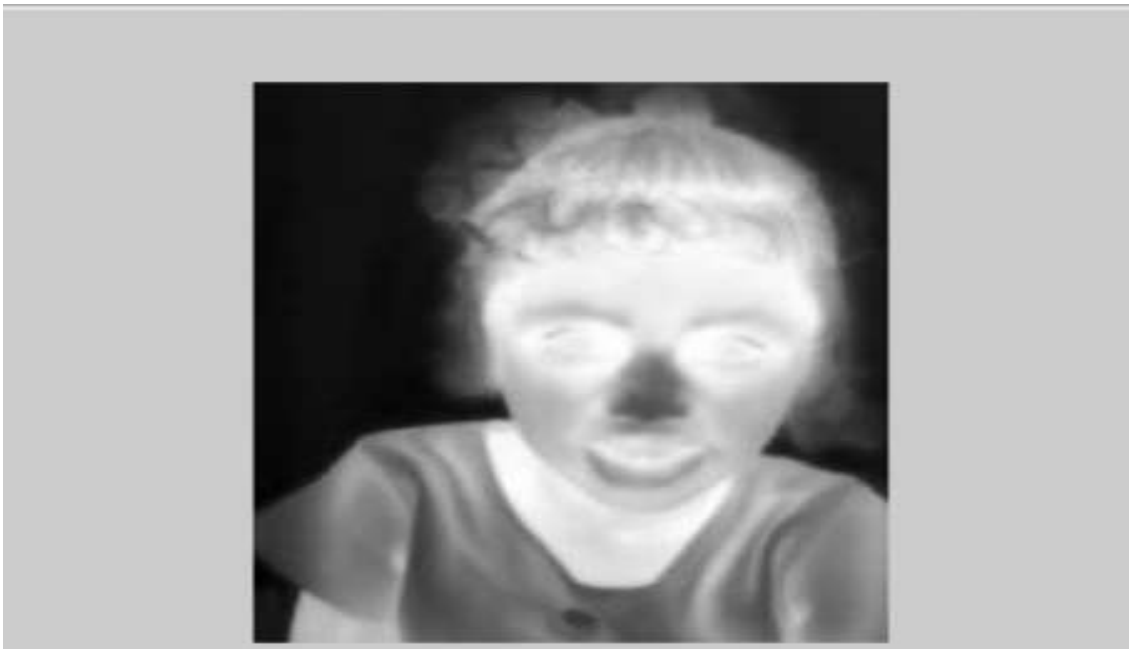

Fig. 3**.** The MATLAB simulation results obtained by comparing the ResNet34 and ResNet18 algorithms. In region growing,opening the initial position of with 241.1799 as initial pixel value. In the region growing ending process it is found 20726 pixels within the threshold range (761 polygon vertices).

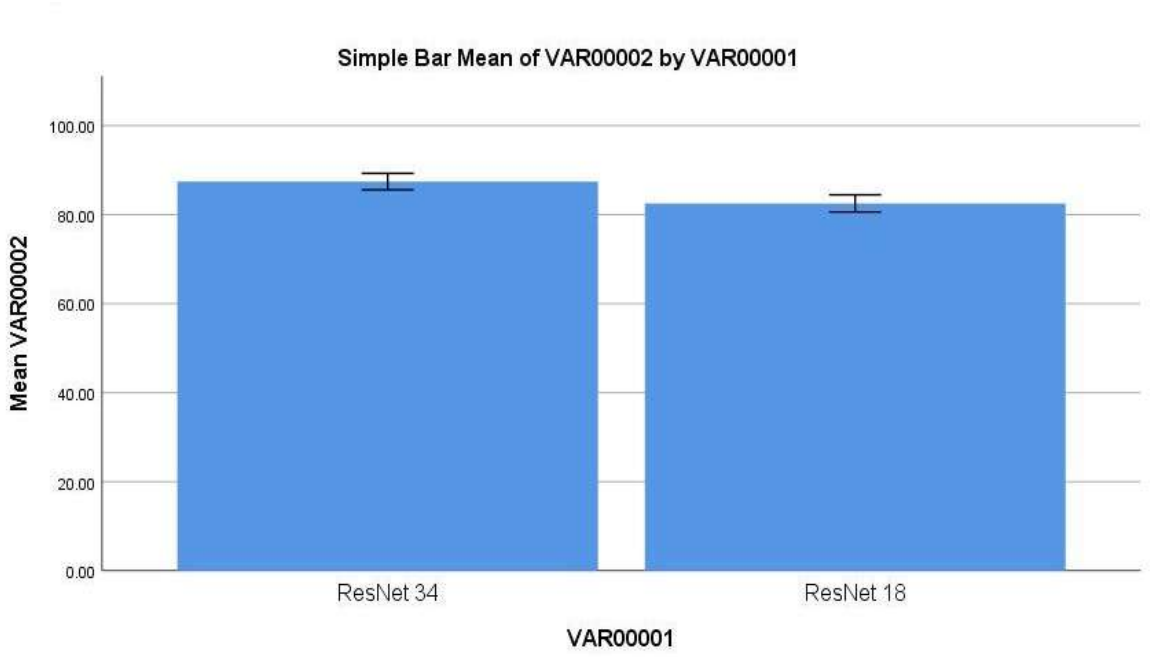

Fig. 4. The performance of ResNet34 has attained greater accuracy of mean 87.4% with the error rate of 0.922 and ResNet18 has accuracy 82.51 % with error rate 0.964. X Axis: ResNet34 vs ResNet18 and Y Axis: mean accuracy with error bars of 95 % CI and $\pm$ 1 SD.