ISSN: 2321-2152

IJMECE

International Journal of modern electronics and communication engineering

E-Mail
editor.ijmece@gmail.com
editor@ijmece.com

www.ijmece.com

IJMECE
ISSN2321-2152
www.ijmece .com
Vol 12, Issue 1, 2024

FACE MASK DETECTION IN REAL-TIME USING PYTHON

Ms. KATIKAKARU PADMA, Assistant Professor, Department Of ECE, SICET, Hyderabad
N.Vamshi, N.Suresh, S.Aravind, P.Naga sai
Department Of ECE, SICE, Hyderabad

ABSTRACT :
Useful tips to help you get started must be followed strictly to prevent the spread of Covid19. In the absence o f effective vaccines and limited medical resources, WHO recommends taking various measures to control the disease and avoid the use of limited medical supplies. Wearing a mask is one of the nonmedical measures that can be used to cut off the main source of SARSCoV2 fluid from patients. Despite controversy over differences between medical sources and masks, all countries have made nose and mouth coverings mandatory for the pu blic. This study aims to develop an effective and fast device that can detect faceless people in public places an d control the mask in order to contribute to public health. The proposed system is a combination of one- and twostage detectors to achieve low reaction time and high accuracy. We use ResNet50 as a framework and use the concept of transfer learning to combine high semantic information across multiple maps. We also high light dynamic changes in the box to improve the performance of the field during face detection. The test is bas ed on our popular basic model. ResNet50, AlexNet and MobileNet. We are exploring the possibility of combi ning this model with design to achieve high results in a short time. The proposed method was found to achieve a high accuracy (98.2%) when using ResNet50. In addition, compared with the current public test model of R etinaFaceMask detector, the proposed model improves the accuracy and recall of face detection by 11.07% an d 6.44%, respectively. The performance of this model is ideal for video devices.

1. Introduction

The 209th report published by the World Health Organization (WHO) on August 16, 2020, states that the new coronavirus (COVID-19) is caused by Severe Acute Respiratory Syndrome (SARS-CoV2) and has infected more than 6 million people. Worldwide. It causes more than 379,941 deaths worldwid e [1]. According to Carissa F. Etienne, Director of the Pan American Health Organization (PAHO), the key to controlling the spread of COVID19 is to stay connected, improve surveillance, and keep sanitation [2]. A rece nt study by researchers at the University of Edinburgh on measures to prevent the spread of the COVID19 pan demic shows that wearing a mask or other covering that covers the nose and mouth can reduce the risk of coro navirus by preventing people from moving forward. .Exhaled air is reduced by more than 90% [3]. Stephen et al. A comprehensive study was also conducted in New York and Washington to evaluate the impact of mask u se by the general population, some of whom were asymptomatically infected. The findings show that even if masks are poor (20% effective), close adoption (80%) could prevent 1745% of expected deaths in the new job within two months and reduce daily deaths by 3458%. 4,5]. Their findings suggested the use of masks to preve nt the spread of coronavirus. In addition, as the country reopens after the Covid19 quarantine, the government and health agencies have recommended wearing masks as an important precaution for public safety. To contro l mask use, technology needs to be developed that forces people to wear masks before going out to public plac es.Mask test means checking whether a person is wearing a mask. Essentially, the problem is reverse engineeri ng of face detection, where different machine learning algorithms are used to identify faces.For security, authe ntication and monitoring purposes. Face detection is an important part of computer vision and pattern recognit ion. Many studies have been done in the past on the complexity of face detection algorithms. The first research on facial recognition was conducted in 2001, using manual feature design and application of machine learning algorithms to train good operators in detection and experience [6,7]. Problems encountered with this method i nclude the complexity of the design and lack of accuracy. In recent years, face detection methods based on dee p convolutional neural networks (CNN) have been widely developed to improve detection [811].Although ma ny researchers are dedicated to creating a good face and know the process, there is a significant ifference betw een "finding a face wearing a face" and "finding a face wearing a face". Based on the existing literature, few st udies have attempted to examine facial expressions. Therefore, the aim of our work is to develop a technology that can identify facial expressions in public areas (e.g. airports, train stations, shopping mall products, bus sto ps, etc.) to reduce the spread of coronavirus and thus contribute to public health. . . In addition, face detection with/without mask in public places is not easy because the available data for face detection is small, which ma kes training models difficult to train. For this reason, the concept of transfer learning is used here to transfer th e content learned from learned networks to similar tasks in the face of many information. The document cover s many faces in a single image, including masked faces, unmasked faces, faces with and without masks, and m ixed images without masks. With a large database of 45,000 images, our technology achieves an accuracy of 9 8.2

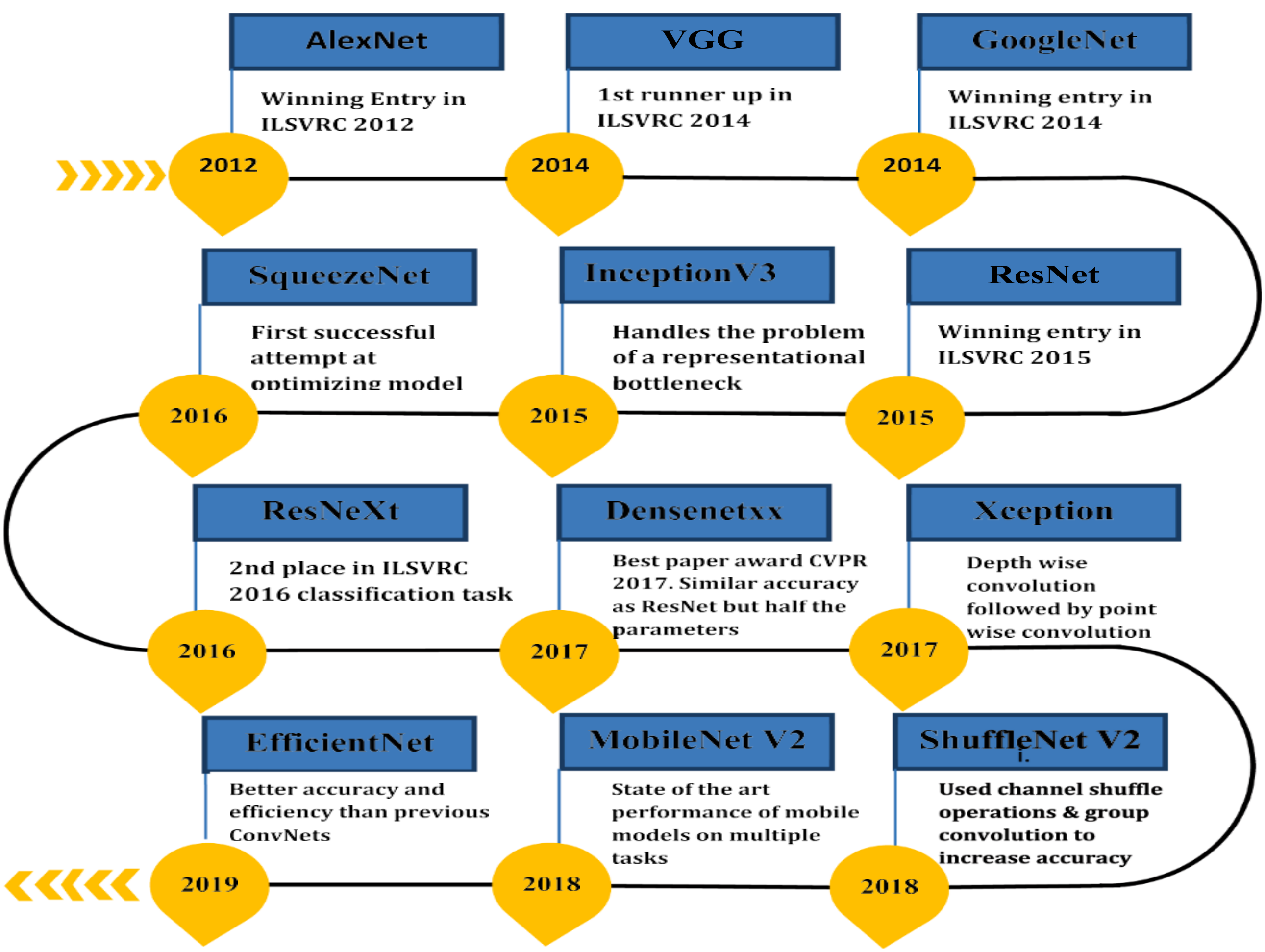


Fig. 1. Various Pre-trained Models based on CNN Architectures.

Basic architecture, number of layers, inference speed, memory consumption and search accuracy. The achieve ments of each model, based on current recommended educational standards for public health, are shown in Fig ure 1. people. This pretraining model must be finetuned using test data. Table 1 gives the number of document s with different features for masked and unmasked faces. A general study of facial information shows that ther e are generally two types of information. These are: i) Masked and ii) Unmasked Dataset. The face mask datas et focuses more on images containing faces with different levels of facial expression and space, while the face-centered dataset

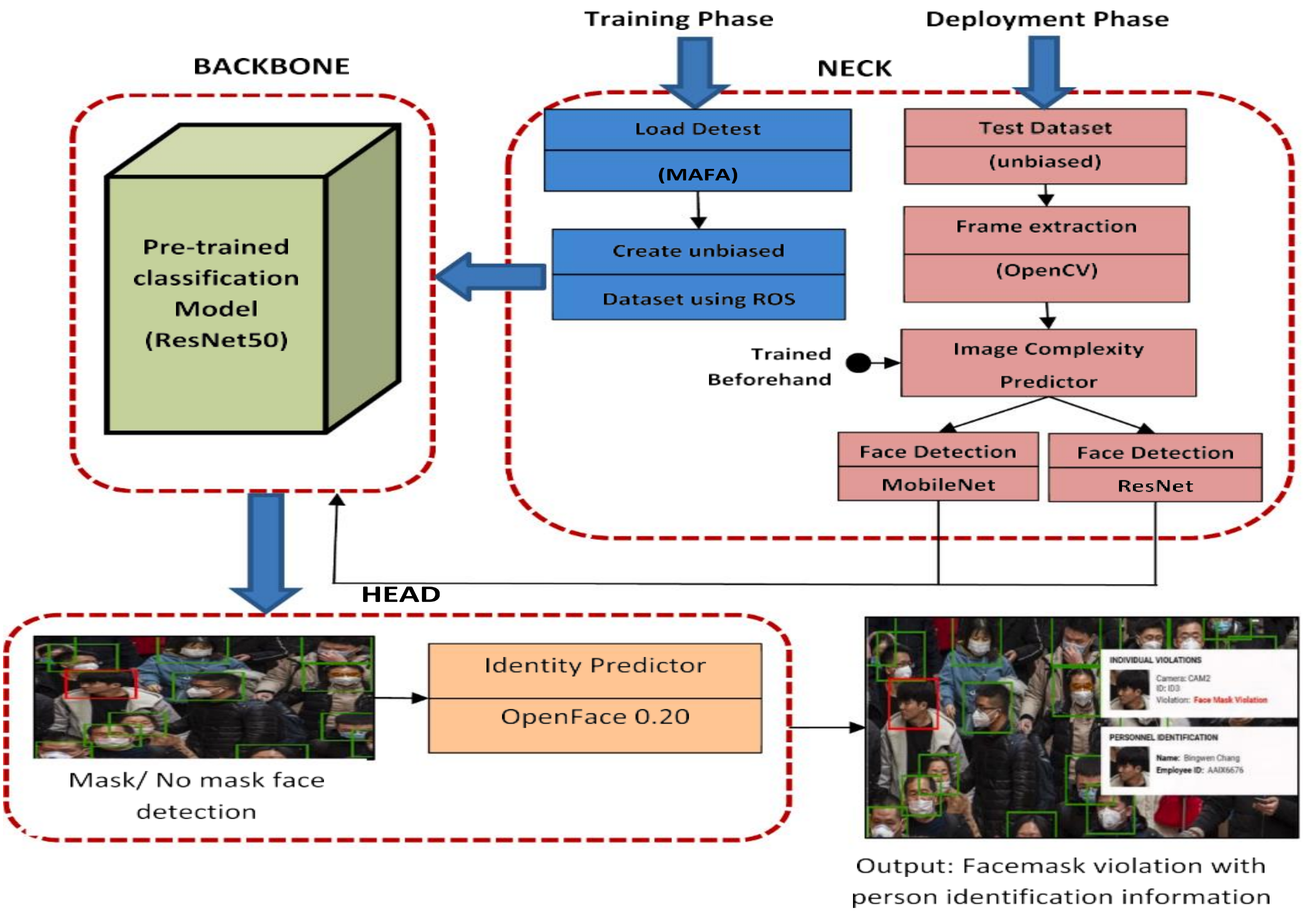


Fig. 2. Proposed Architecture.

Such facial features are often characterized by their congestion and location close to the nose and mouth. Tabl e 1 shows these two popular documents.

Proposed Architecture

The proposed architecture is based on the object recognition parameters given in [38]. Based on these principl es, all activities related to the object recognition problem can be combined according to three elements: bones, neck and head, as shown in Figure 2. Here the spine corresponds to the underlying convolutional neural netw ork. extraction of features. Get information from photos and turn it into custom reports. In the proposed archit ecture, the concept of transfer learning is applied to the backbone to use material already learned by powerful prelearned convolutional neural networks to extract new features from the model.One of the best methods in t he system, which includes three popular pretraining models such as ResNet50, MobileNet and AlexNet, is to g et the best results in face detection. ResNet50 was found to be the best choice to form the backbone of the pro posed model (see Section 4.2). The novelty of our study is presented in the neck component. The middle comp onent, Neck, contains all the preliminary work that needs to be done before the image is classified. To ensure our models work well with monitoring tools, Neck uses different pipelines during the training and delivery ph ase. The training process is based on generating unbiased private data and improving ResNet50. The pipeline i ncludes video extraction from video, followed by face detection and removal. To achieve the balance between face detection accuracy and computation time, we propose a blurred image approach (see Section 3.3). Last co mponent, title

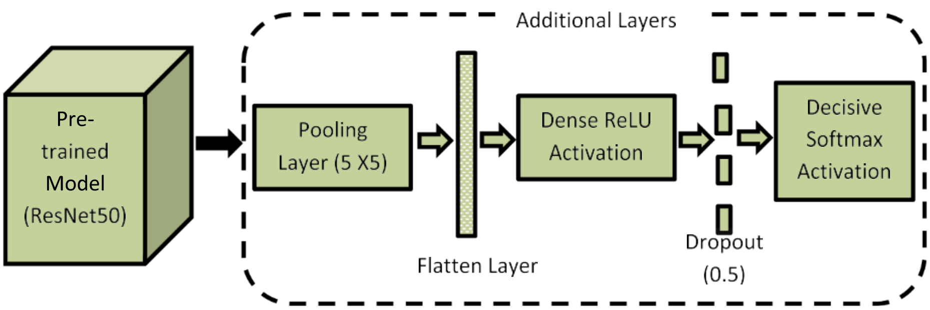


Fig. 3. Fine-tuning of ResNet50.

3.1. Creating an unbiased mask dataset

The mask-
centered dataset, MAFA [35], was initially considered to have a total of 25,876 images divided into two group s: masked and unmasked. The number of images covered in MAFA is 23,858, while the number of disapprove d images is only 2018. It has been observed that MAFA has a class conflict problem that will show bias for m ost classes. Therefore, an ablation study was performed once using the original MAFA (biased) and then the d ataset (unbiased) to verify the performance of the image classifier. 3.1.1

ISSN2321-2152
www.ijmece .com
Vol 12, Issue 1, 2024

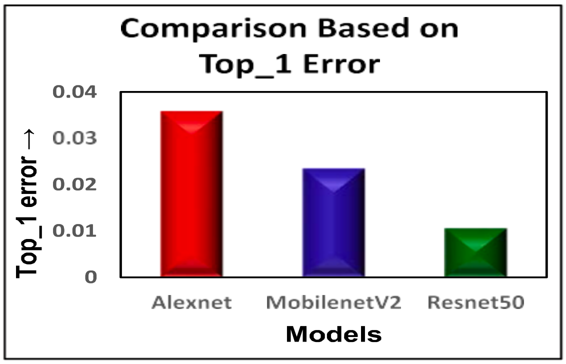
Fig. 4. Variety of Occlusions Present in Dataset.

Caffe python library [7]. In summary, our CNN model almost matches the performance of Madhura et al. [11], achieving the highest error rate of 1.8% higher in the MAFA validation set. This discrepancy may be due to a simplistic approach to training.

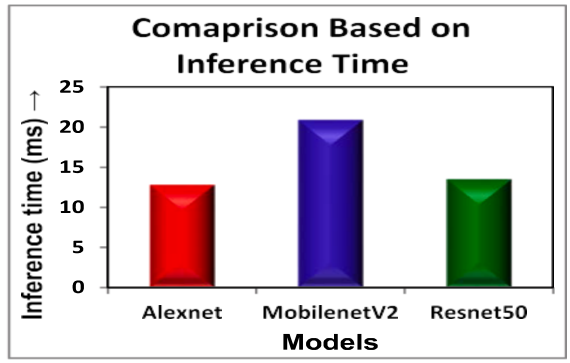
4.2. Model Comparison

As discussed in Section 3.2, we can apply transfer learning to a previous learning model for image classificat ion, but the open question is how to decide which model is good for our job. In this section we compare our p erformance models. ResNet50, AlexNet and MobileNet according to the following standards:

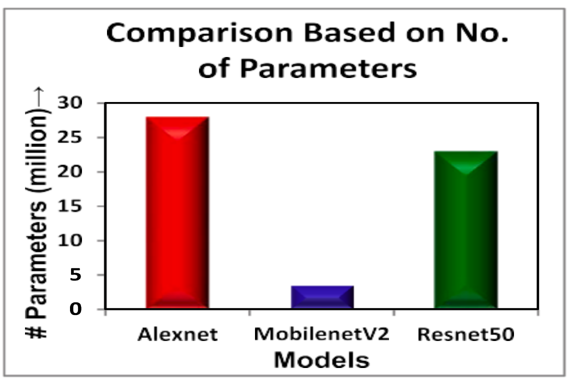
1. Top 1 error: This type of error occurs when the predicted class with the highest confidence differs from the actual class.
2. CPU inference time: The time it takes for the model to predict the category of the input image, that is, start ing from reading the image, performing all intermediate transformations, and finally generating the high conf idence category. The picture belongs.
3. Number of parameters: All topics are included in each layer of the model. These parameters directly affect predictive power, model complexity, and memory usage [45]. This information is useful for understanding t he minimum amount of memory required for each model. Also he



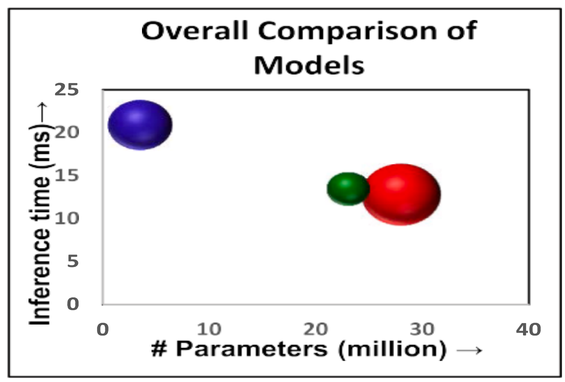
(a) Top_1 error



(b) Inference Time (CPU)

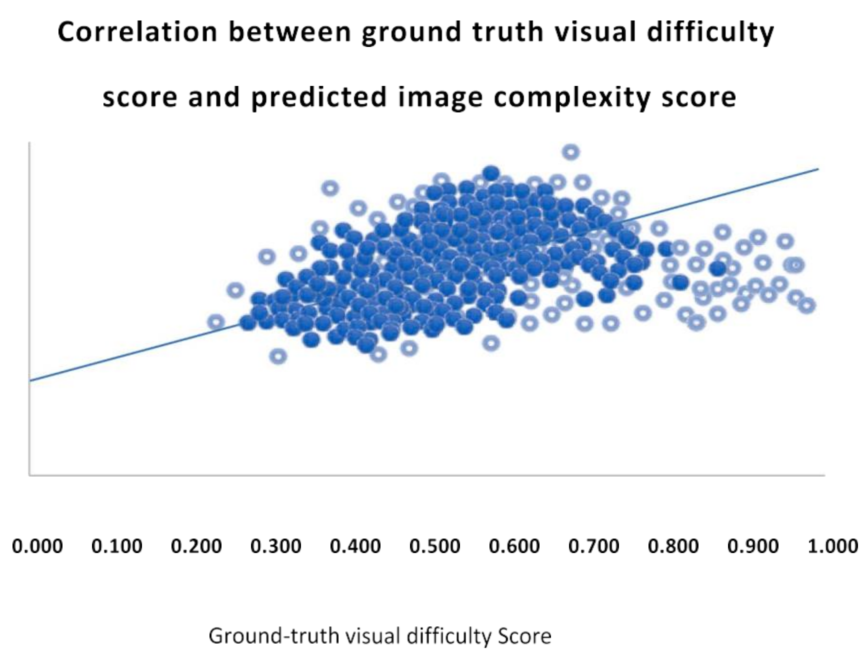


(c) Model Size



(d) Overall Comparison

Fig. 7. Comparison of Various Models on Different Performance Criteria.



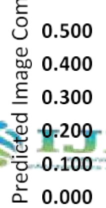


Fig. 8. Correlation between Ground Truth Visual Difficulty Score and Predicted Image Complexity Score.

This was confirmed by Simone Bianco and others. get. We need a large number of training parameters to ens ure the balance between model accuracy and memory usage [45].
A model with the least errors in the top-
1, less CPU inference time and the number of defects will be considered a good model for our study.
Confusion matrices of different models during the testing process are shown in figure 6. The actual comparis on of various models with respect to Top1 error is shown in figure 6. 7(a). As can be seen from the figure, Al exNet has more errors, while ResNet50 has the lowest error. We then compare the models in terms of inferen ce time. Test images are fed into each model and the inference time across all iterations is averaged. It can be seen from the picture. As can be seen from Figure 7(b), MobileNet requires more time to extract images, wh ile ResNet and AlexNet spend almost the same time for image extraction. Additionally, the memory usage of the base model is compared by calculating the number of failed subjects. These parameters can be obtained by creating a content model for each model in Google colab. Figure 7(c) shows that the number of parameter s in AlexNet for our particular dataset is approximately 28 million. Additionally, the number of non-
MobileNet and ResNet 50 is around 3.5 million and 25 million respectively.After analyzing the performance of each model against various models,We will condense all these points into an empty bubble form. X coordi nate is the parameter and Y coordinate is the inference time. The large bubble represents the Top-
1 error (the smaller the bubble, the better). The overall comparison of each model is shown in the bubble dia gram in Figure 7(d).It can be seen from Figure 7(d). 7. Smaller bubbles are better for accuracy, while bubbles closer to the origin are better for memory and thinking speed. Now the answer to RQ1 can be given as follo ws:AlexNet has a high error rate. MobileNet is slow to make decisions.
ResNet50 is the best choice in terms of accuracy, speed and memory usage when detecting masks using trans formation learning.

4.3. Evaluating the effectiveness of complex image Predictor

We use Kendall coefficient α (tau) to evaluate the effectiveness of complex image. We calculated the Kendal l rank correlation coefficient α between the estimated visual difficulty score and the actual perceived difficult y on the ground. The Kendall rank correlation coefficientis suitable for our analysis as it does not differ betw een different types of competition. Based on the characteristics of the image, each annotator assigns a difficul ty score to the image based on the image's difficulty score range. Kendall rank correlation coefficients were c alculated using the kendalltau()SciPy function in Python. This function takes two scores as parameters and re turns the correlation coefficient. Our experts obtained the Kendall correlation coefficient α as 0.741; This me ans that it is not easy to predict the performance of the image. It can be seen from the picture. As can be seen from Figure 8, there is a very good correlation between the ground truth and the estimated difficulty scores.F urther in Figure 8, it can be seen that the cloud points form a skewed Gaussian distribution and their main poi nts follow the diagonal line, confirming the relationship between the two points.

Particularly, the proposed model generates 11.75% and 11.07% higher precision in the face and mask detection respectively when compared with Retina FaceMask. The recall is improved by 3.05% and

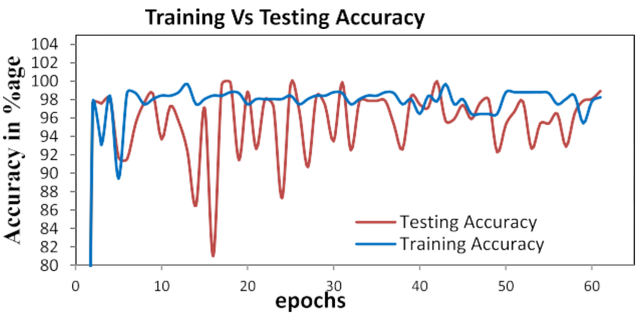


Fig. 10. Training and Testing Accuracy over 60 Epochs.

6.44% in the face and mask detection respectively. We had observed that improved results are possible due to optimized face detector discussed in Section 3.3 for dealing with complex images.

5. Conclusions

This study proposes a deep learning method to detect facial expressions in public places to prevent the spread of coronavirus in society. The proposed system effectively achieves occlusion in severe conditions by using a group of single-
and twolevel detectors at the preprocessing level. The combination method not only helps in achieving high a ccuracy but also makes it very fast. Additionally, adaptive learning is applied to pre-
trained models and multiple experiments are performed on conflicting data, resulting in high efficiency and lo w cost. Facial recognition further violates the masking law and turns the body into a public presence.
Finally, this study opens up interesting directions for future researchers.First of all, the technology can be inte grated into a highdefinition video surveillance device, including but not limited to face detection. Secondly, th e model can be extended to include to be, to be, to be, to be cut to be cut to be cut to be cut
Credit Author Guideto be done to be cut by Shilpa Sethi: Design, Process, Author -
Original . Mamta Kathuria: Data curation, Conceptualization, Writing –
first draft. Trilok Kaushik: Career.Declaration of Competing InterestsThe authors declare that they are not aw are of any competing financial interests that might appear to have influenced the work published in this article Interests or personal relationships.

References

Allen, I. E., & Seaman, J. (2008). ***Staying the course: Online education in the united states, 2008.*** ERIC.

Bambrick-Santoyo, P. (2010). ***Driven by data: A practical guide to improve instruction***. John Wiley & Sons.

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2023). ***lme4: Linear mixed-effects models using eigen and S4***. https://github.com/lme4/lme4/

Betebenner, D. W. (2021). ***randomNames: Generate random given and surnames***. https://CenterForAssessment.github.io/randomNames

Bransford, J. D., Brown, A. L., Cocking, R. R., et al. (2000). ***How people learn*** (Vol. 11). Washington, DC: National academy press.

Breiman, L. (2001). Random forests. ***Machine Learning***, ***45***(1), 5–32.

Bryan, J. (2017). ***Project-oriented workflow***. https://www.tidyverse.org/blog/2017/12/workflow-vs-script/

Bryan, J. (2019). ***Reproducible examples and the 'reprex' package***. https://community.rstudio.com/t/video-reproducible-examples-and-the-reprex-package/14732

Bryan, J. (2020). ***Happy git with r***. https://happygitwithr.com/

Bryk, A. S., Gomez, L. M., Grunow, A., & LeMahieu, P. G. (2015). ***Learning to improve: How america's schools can get better at getting better***. Harvard Education Press.

Campaign, D. Q. (2018). ***Teachers see the power of data - but don't have the time to use it***. https://dataqualitycampaign.org/wp-content/uploads/2018/09/DQC_DataEmpowers-Infographic.pdf

Conway, D. (2010). The data science venn diagram. ***Drew Conway***, ***10***. http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram

Datnow, A., & Hubbard, L. (2015). Teachers' use of assessment data to inform instruction: Lessons from the past and prospects for the future. ***Teachers College Record***, ***117***(4), n4.

Dirksen, J. (2015). ***Design for how people learn***. New Riders.

Dweck, C. (2015). Carol dweck revisits the growth mindset. ***Education Week***, ***35***(5), 20–24.

Education Statistics U.S. Department of Education, N. C. for. (2019). Concentration of public school students eligible for free or reduced-price lunch. ***The Condition of Education 2019***. https://nces.ed.gov/fastfacts/display.asp?id=898

Elbers, B. (2020). ***Tidylog: Logging for dplyr and tidyr functions***. https://github.com/elbersb/tidylog/

Emdin, C. (2016). ***For white folks who teach in the hood... And the rest of y'all too: Reality pedagogy and urban education***. Beacon Press.

Estrellado, R. A., Bovee, E. A., Motsipak, J., Rosenberg, J. M., & Vel'asquez, I. C. (2019). ***Taylor and francis book proposal for data science in education***. https://github.com/data-edu/DSIEUR_support_files/blob/master/planning/T%26F%20Book%20Proposal%20for%20Data%20Science%20in%20Education.docx

Estrellado, R., Bovee, E., Mostipak, J., Rosenberg, J., & Vel'asquez, I. (2024). ***Dataedu: Package for data science in education using r***. https://github.com/data-edu/dataedu

Firke, S. (2023). ***Janitor: Simple tools for examining and cleaning dirty data***. https://github.com/sfirke/janitor

for Education Statistics, N. C. (2018). ***Public elementary/secondary school universe survey***. https://nces.ed.gov/programs/digest/d17/tables/dt17_204.10.asp?current=yes

Gelman, A., & Hill, J. (2006). ***Data analysis using regression and multilevel/hierarchical models***. Cambridge university press.

Grimm, K. J., Ram, N., & Estabrook, R. (2016). ***Growth modeling: Structural equation and multilevel modeling approaches***. Guilford Publications.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). ***The elements of statistical learning: Data mining, inference, and prediction***. Springer Science & Business Media.

Hattie, J. (2012). ***Visible learning for teachers: Maximizing impact on learning***. Routledge.

Healy, K. (2019). ***Data visualization: A practical introduction***. Princeton University Press.

Hill, A. (2017). ***Up and running with blogdown***. https://alison.rbind.io/post/2017-06-12-up-and-running-with-blogdown/

Hirschberg, J., & Manning, C. D. (2015). Advances in natural language processing. ***Science***, ***349***(6245), 261–266.

ISSN2321-2152
www.ijmece .com
Vol 12, Issue 1, 2024

Ismay, C., & Kim, A. Y. (2019). ***Statistical inference via data science***. CRC Press.
James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). ***An introduction to statistical learning*** (Vol. 112). Springer.
Jarvis, C. (2019). ***Creating calling***. HarperCollins.
Jordan, R. (2015). ***High-poverty schools undermine education for children of color***. https://www.urban.org/urban-wire/high-poverty-schools-undermine-education-children-color
Kahneman, D. (2011). ***Thinking fast and slow***.
Kearney, Michael W. (2016). Rtweet: Collecting twitter data. ***Comprehensive R Archive Network. Available at: Https://Cran. R-Project. Org/Package= Rtweet***.
Kearney, Michael W., Revilla Sancho, L., & Wickham, H. (2023). ***Rtweet: Collecting twitter data***. https://docs.ropensci.org/rtweet/
Kleon, A. (2012). ***Steal like an artist: 10 things nobody told you about being creative***. Workman Publishing.
Kozol, J. (2012). ***Savage inequalities: Children in america's schools***. Broadway Books.
Krist, C., Schwarz, C. V., & Reiser, B. J. (2019). Identifying essential epistemic heuristics for guiding mechanistic reasoning in science learning. ***Journal of the Learning Sciences***, ***28***(2), 160–205.
Kuhn, M. et al. (2008). Building predictive models in r using the caret package. ***Journal of Statistical Software***, ***28***(5), 1–26.
Kuhn, M. (2023). ***Caret: Classification and regression training***. https://github.com/topepo/caret/
Kurz, S. (2019). ***Statistical rethinking with brms, ggplot2, and the tidyverse***.