Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

Face To BMI: Predicting Body Mass Index Using Neural Networks

G Lavanya[1], M Kushal[2], G. Gayathri[2], M. Revanth[2]

[1]Assistant Professor, Department of Artificial Intelligence and Data Science, Vignan Institute of Technology and Science, Hyderabad, India

[2]UG Student, Department of AI&DS, Vignan Institute of Technology and Science, Hyderabad, India

Correspondence

G.Lavanya

Assistant Professor , Department of Artificial Intelligence and Data Science, Vignan Institute of Technology and Science, Hyderabad, India

- Received Date: 25 May 2025
- Accepted Date: 15 June 2025
- Publication Date: 27 June 2025

Keywords

Facial Image Analysis, Deep Learning, BMI Prediction, Health Monitoring.

Abstract

Body Mass Index (BMI), a vital health metric indicating weight relative to height, classifies individuals as underweight, normal weight, overweight, or obese, guiding early interventions for health risks, but traditional methods relying on height and weight measurements are labor-intensive, making automated BMI assessment a scalable and efficient alternative for health analysis and decision-making; leveraging facial features, which reveal correlations between face geometry and BMI, we employed large-scale pre-trained models like EfficientNet-B7, Swin-Transfomer, and ResNeSt- 101, trained on diverse datasets such as the Illinois DOC, Height-weight-BMI dataset with Celebrity Faces, to enhance prediction accuracy, scalability, and applications in health monitoring, insurance, and policymaking, thereby enabling informed societal and individual health decisions..

Introduction

Body Mass Index is an essential measure of the body weight of a person to his height and reveals how healthy the person is. It is mostly known to be linked with physical health, psychological well-being, and even to social dynamics. The BMI classification describes whether the person is under weight, normal weight, obese or, overweight, and it can be helpful in taking early interventions in case the risks arise from health concerns. The traditional method for finding BMI depends on measured height and weight of an individual. Though the method applied to a single person is so simple, this method becomes clumsy for the application for large populations because the whole BMI process of computation involves equipment plus manual procedures involved in collecting weights and heights measurement. Instead, automated BMI assessing methods are scaled up and, therefore, supply useful information about health-related social analysis and supports decision-making from organizational and policy levels.

There has been quite a lot of developments during the past few years as regards the manner in which technology can make predictions about BMI through facial features. The faces of humans represent meaningful patterns, which are highly correlated with BMI; higher BMI is often correlated with wider structures of the face, especially within the middle and lower parts of it, and vice versa- lower BMI often corresponds to a thinner facial appearance. Previous work has explored BMI prediction from geometric facial features or deep learning-based approaches. However, most of them are constrained by smaller, more limited datasets so don't quite generalize as well to populations.

In this research, we aim to overcome these limitations by leveraging large-scale pre-trained models that have showed great performance in computer vision related tasks. Specifically, we employ models such as EfficientNet-B7, Swin-Transformer, and ResNeSt-101, which are state-of-the-art architectures known for their robustness, scalability, and efficiency in feature extraction. To train our models, we utilize the Illinois DOC labeled faces dataset, a rich dataset that contains facial images labeled with corresponding BMI values. For evaluation, we use additional dataset— Height-weight-BMI dataset with Celebrity Faces to test the generalizability and reliability of our approach across varied data distributions.

Our proposed method introduces a significant advancement in BMI prediction by combining large-scale pre-trained models like EfficientNet-B7, Swin-B, and ResNeSt-101 with diverse datasets. This approach not only improves prediction accuracy but also ensures scalability, making it suitable for large-scale applications. Reliable BMI prediction methods such as ours hold promise for a range of practical applications, including health monitoring, insurance assessments, and policy

Citation: Reddy SR, Prashanth M, Yadav GR, Reddy MJ. Human Computer Interaction Through Eye Ball. GJEIIR. 2025;5(4):073.

development, ultimately contributing to better health outcomes and informed decision-making at both individual and societal levels.

Hence, while the camera continuously delivers real-time video feed, it analyzes eye landmarks through time to trigger movements such as clicks left and right or scrolling. It also becomes very interactive since it becomes quite like using a mouse with an eye [5]. It is now integrated with vocal recognition to even make it easier. For instance, opening an app,dictating something, or controllingvolumecould be made possible by voice. And combined with eye-gesture commands, the system becomes more powerful because it can give such freedom to users in totally not touching the computer. It is a total breakthrough for the mobilities impaired because itcomes in that genuinely hands-free interface with technology [6]. It is a highly adaptable system which learns and modifies itself according to the unique eye movement pattern of the individual user and becomes more precise and personalized over time in usage. It improves the more it is used, so that every person is getting the most seamless experience possible. Furthermore, because it features real-time feedback, itbecomes more like an extension of the human body and feels immediate to each eye movement [7]. Be it a person sitting at home in a study or sitting in a clinic, the system understands the needs of a person and delivers a smooth experience. Dynamic filtering techniques are also at work to ensure precise tracking of eye movements even under adverse lighting conditions. So whether it's a dimly lit room or bright fluorescentlights, thesystem keeps working. Havinglarge-eye with small movements brings precise and various capabilities to the system—reading documents or browsing websites [8].

This system is so fast that when it comes to responsiveness, it's almost classless. Real-time processing creates no delay at all between eye movement and processes on the screen, givingmuch smoother performance with reduced frustrations. This is highly of use to users depending on the system to carry out their everyday activities. Now, they can do it much faster and at the same pace as using a mouse [9]. The machine learning algorithms will even learn very small eye movements, translating these into cursor movements on screen; thus, the user will have control over the cursor no matter how much effort is used.

Additionally, the complete system is customized. Users can set the sensitivity of the eye-tracking feature, whether they want the micromanaging fine-tuning of movements for delicate tasks or fast operation responding for gross movements. The flexibilityofthe system is such thatit can learnand then recognize favorite gestures like specific bangs or areas for invoking specificactions [10]. This way, the end-users will be really personalized, with experiences that are really tailored to meet their requirements.

The long-term aim of this technology is simply to make computers available for those who are physically disabled. Eye contact system is such that it ends up removing traditional input systems, allowing those who struggle with some sort of ability deprivation to use it for whatever it is that they may want to do-online possible working, learning, or playing. For everyone, this means having a much more extensive experience with computers for effective and independent operation.Thisis very much in the direction of using eye-tracking, voice recognition, and real-time processing all together to take steps toward creating a culture in which society has as much exposure to technology as possible.

Contribution

To enhance the BMI prediction from a face using a large dataset. The following are the contributions of this paper:

- Identify the correlation between BMI and human faces and come up with a new approach to predict BMI from human faces using deep learning and transfer learning models like EfficientNet-B7, Swin-B, and ResNeSt-101. Our approach is illustrated in Fig. 1 above
- We used 2 publicaly available datasets which contain images along with the corresponding BMI values of Hollywood Celebrities and Jail prisoners. And we applied our methods on those datasets and improved the Mean Absolute Error (MAE).

Section II will briefly introduce a review of the related work. It will mainly state the primary approaches and methodologies in brief. Section III will deal with the methodology proposed in the study. The section will be titled "Experiments," with details regarding the datasets, the experimental setup, and evaluation of the methodology proposed in Section IV. Section V will summarize results and conclusions developed from the study. Finally, Section VI shall be a section for concluding remarks.

Literature Survey

In an attempt to derive BMI, Wen and Guodong [2] used computation techniques in processing images of the faces. The approach identified the face features by utilizing Active Shape Model, which gave rise to seven distinctive features including Eye Size, Cheek to Jaw Width Ratio, Perimeter to Area Ratio, Width to Upper Facial Height Ratio, Lower Face to Face Height Ratio, and Mean-Eyebrow-Height. They made use of Support-Vector-Regressor, Least-Squares-Estimation, and Gaussian-Process in the training and testing of models on regression tasks with the Morph II dataset. Among these, SVR delivered the most accurate predictions. Expanding on this, Barr et al. [3] developed a method to compute Facial BMI (fBMI) and evaluated its correlation with actual BMI. Their results demonstrated stronger correlations in normal and overweight categories, though the accuracy decreased in underweight and obese groups. Their feature extraction, however, was limited to facial landmarks, suggesting potential improvements by incorporating additional visual features.

E. Kocabey et al. [4] they proposed an approach based on deep learning that predicts BMI based on facial images from the paper VisualBMI. They tested 4,206 images for feature extraction using Visual Geometry Group-Net and Visual Geometry Group-Face models and employed epsilon-ESP-B version of Support Vector Regression for BMI prediction. Results: Pearson correlation coefficients were 0.71 for males, 0.57 for females and 0.65 for overall categories using VGG-Face was better than VGG-Net.Furthermore human evaluations outfought the machine prediction for lower BMI Values, even though predictions were at par with high BMI categories.

A. Haritosh et al. [5] proposed a new technique for estimating height, weight and BMI from facial images. Their study utilized 4,206 images taken from the VisualBMI dataset and also 982 images from Reddit HWBMI dataset. They applied the Viola-Jones algorithm to crop facial images to 256 × 256 pixels. A feature extractor processed these images, followed by a 3- layer ANN model for predictions. XceptionNet achieved MAE values of 4.1 and 3.8 for BMI on the VisualBMI and Reddit HWBMI datasets, respectively, while height and weight predictions also showed promising accuracy with VGG-Face and XceptionNet.

C. Mayer et al. [6] examined how Body Mass Index and waist to hip ratio are related to facial features. They analyzed 49 standard images of women, with Body Mass Index (BMI) ranging from 17.0 to 35.4 and WHR between 0.66 and 0.82. Using 119 anatomical landmarks and semi landmarks identified through TPSDig software and a sliding landmark algorithm, they explored facial shapes and textures. Multivariate linear regression revealed that facial shape predicted 25% of BMI variation, while facial texture accounted for 3-10%. Their findings indicated that facial features were more predictive of BMI than WHR.

Jiang Min et al. [7] investigated geometry-based as well as deep learning methods for BMI prediction, examining influence of the factors like gender, and head orientation. While deep learning methods outperformed geometrybased approaches, the higher dimensionality of the features hindered performance when training data was limited. Additionally, significant variations in head poses led to reduced accuracy. Their research employed the Morph II dataset alongside the FIW-BMI dataset, which they compiled using images from the social media.

H. Siddiqui et al. [8] investigated a custom convolutional neural network for estimating BMI and utilized pre- trained Convolutional neural network models, including Visual Geometry Group -19, ResNet, Dense-Net, Mobile-Net, and Light-CNN. Extracted features were passed through Support-Vector-Regressor and Ridge-Regression for prediction. Using Visual-BMI, VIP Attributes, and Bollywood datasets, they reported MAE values ranging from 1.04 to 6.48. Among the models, DenseNet and ResNet combined with Ridge Regression performed the best. Pre-trained models slightly outperformed their custom end to end CNN.

Methodology

Preprocessing Data

In our project, we have utilized frontal -facing images from the dataset to predict BMI. Variations such as tilted head positions, inconsistent zoom levels, and differences in lighting were present across the dataset. To address these challenges, we applied a preprocessing pipeline tailored to our approach.

Initially, faces were detected and extracted using pre-trained facial detection models like MTCNN and others. Cropped facial regions were used as the input to the model ensuring consistency across all input images. Unlike earlier methods that blurred the surroundings, our approach focused mainly on normalizing the face size while preserving facial details for accurate feature extraction by the model. And also included some techniques like flipping, rotation and others.

Figure 1. *Input image and Preprocessed image*

Transfer Learning Concept

Body Mass Index calculation from face images is complex, and training the necessary features from small datasets is not accurate. To enhance performance of model and also reduce training time, we have utilized transfer learning with state of art of pre-trained models:

EfficientNet: EfficientNet contains a family of different models that balance accuracy, efficiency by scaling depth, width, and resolution systematically. It was trained on the ImageNet database and achieves superior performance while using fewer parameters compared to conventional architectures. This model is highly efficient for facial image feature extraction and BMI prediction.

Swin Transformer: The Swin Transformer model applies transformer-based architecture to computer vision tasks. It utilizes shifted windows for efficient computation and achieves excellent performance on image-based tasks. Pretrained on the ImageNet dataset, it captures global dependencies and local features effectively, making it well-suited for BMI estimation.

ResNeSt: ResNeSt introduces a split-attention mechanism into the ResNet architecture, enabling the model to adaptively capture feature representations at multiple granularities. Trained on the ImageNet dataset, it delivers high accuracy while maintaining computational efficiency, making it a robust choice for feature extraction from facial images.

Training Process

We have used fully connected layers concept at the ending of all the pre trained models. Output from the pre-trained backbone was first processed using Global Average Pooling to decrease the dimensionality and gain only the most important and relevant features.

To prevent the overfitting problem, we have incorporated a dropout layer with dropout rate of 50% in the model's architecture. For the Activation-function, we have utilized the Gaussian Error Linear Unit, which will combine the properties of rectified linear unit activation, Dropout, and the Zoneout. This activation function generalizes better in the presence of noise and improves performance on complex datasets like ours.

Since our study employed a comparatively larger dataset, we fine-tuned the pre-trained models to maximize feature extraction. The deeper layers of convolutional neural networks, closer to the output, were fine-tuned with a lower learning rate to retain the learned complex features from the pre-trained models, while the newly added fully connected layers were trained with a higher learning rate to quickly adapt to the task of BMI prediction.

We employed the Adam-optimizer with learning rate scheduled to progressively decrease learning rates across deeper layers, ensuring smooth convergence during training. To implement this, we used the MultiOptimizer utility from TensorFlow Addons. This helped effectively optimize the combined architecture and enhance the BMI prediction accuracy.

Experiments

Datasets Used

We have evaluated the proposed methodology of ours on two public datasets which are mentioned below.

Illinois DOC labelled faces Dataset

The Illinois Department of Corrections labeled faces dataset is the collection of images and related metadata sourced from the Illinois Department of Corrections. Dataset consist of front and side faced photographs of nearly around 68,149 individuals. Each entry includes additional details such as gender, height, weight, and date of birth. During preprocessing, 1,365 corrupted images and 7,309 entries lacking height and weight data were excluded. The final dataset used for research comprised 56,200 male and 3,649 female subjects. The average Body Mass Index (BMI) across the dataset was calculated to be 27.88, with a standard deviation (S.D) of 5.20. The refined dataset served as the foundation for training and validating machine learning models. Example images from the dataset illustrate its structure and content.

Figure 1. *Illinois DOC labeled faces Dataset*

Height-weight-BMI dataset with Celebrity Faces

The Height-Weight-BMI Dataset with Celebrity Faces consists of images of 50 celebrities, accompanied by biometric attributes such as height, weight ,and calculated Body Mass Index (BMI). This dataset comprises of 15 female and 35 male subjects. The average BMI was computed to be 23.95, with a standard deviation of 2.18. The finalized dataset provides a reliable source for training and validating models in biometric and health- related research. Example images from this dataset are shown in the corresponding visual references.

Figure 3: Height-weight-BMI dataset with Celebrity Faces

Experimental Setup Used

We used the Kaggle notebook that has 16 GB RAM and 100 GB ROM with T4 x2 accelerator. Overfitting is avoided by using Early Stopping Mechanism, stopping the training process when validation loss is no more improving at an interval of the same 5 repeated epochs.

Evaluation Metrics Used

In this paper, we utilized the Mean Squared Error as the regression of loss function. This metric, defined in Equation (1), will calculate the avg of the squared difference between the actual values (yi) and the predicted values (xi), divided by the total number of samples (n). The squaring of the differences ensures that larger errors are penalized more significantly, making MSE an effective choice for regression tasks.

We assessed our model's performance using the Mean Absolute Error, which is computed by taking the avg of the absolute difference between the actual values (yi) and the predicted values (xi), over all samples (n).

$$MSE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - x_i)^2 \qquad (1)$$

Result

Here, we compared the performance of different models using two evaluation metrics: Mean Squared Error and Mean Absolute Error. For consistency, we have focused on MAE in our analysis. The tables present the MAE results for different models across various datasets, with Overall-MAE representing the Mean Absolute Error on the complete dataset, and Male-MAE and Female-MAE showing the Mean Absolute Error values for male and female respectively.

Table 1. *MAE- Results of Illinois Doc labeled faces Dataset*

	Overall-MAE	Male-MAE	Female-MAE
EfficientNet	2.87	3.12	2.58
Swin Transformer	3.02	2.92	3.10
ResNeSt	3.15	3.05	3.20

Table 1 represent the performance of our model, Illinois Doc Labeled Faces dataset containing of facial images, and the Overall-MAE for this dataset was found to ranging from 2.87 to 3.15. For the male subset, the MAE values ranged between 3.05 and 3.12, while for the female subset, the MAE was higher, ranging between 2.58 and 3.20. Among the models evaluated, EfficientNet demonstrated the best performance with the lowest MAE for both overall and gender-specific results.

Table 2. MAE results of Height-weight-BMI dataset with Celebrity Faces

	Overall-MAE	Male-MAE	Female-MAE
EfficientNet	3.94	3.05	3.42
Swin Transformer	3.25	3.29	3.02
ResNeSt	3.75	4.02	3.74

Table 2 represent the performance of our model, Height-Weight-BMI Dataset with Celebrity Faces dataset, which includes images with associated height, weight, and BMI labels, and the MAE-Overall for this dataset ranged from 3.42 to 3.94, while the male subset had MAE values between 3.05 and 4.02, and the female subset had values between 3.02 and 3.74. Among the models evaluated, Swin Transformer demonstrated the best performance with the lowest MAE for both overall and gender-specific results.

Conclusion

In our study, we recognized that individuals with higher BMI values are at a greater risk of developing various health problems. We also discovered the significant correlation between BMI and the facial features. To leverage this relationship, we proposed an innovative approach for predicting BMI based on facial images using deep learning techniques.

Our approach involved evaluating the model on two public available datasets from different domains, including images of jail prisoners and the Hollywood Celebrities. The facial data was preprocessed to ensure proper alignment and preparation for model training. To enhance processing speed and efficiency, we utilized GPU (Graphic Processing Unit) acceleration and transformed our image data into TensorFlow Record format for optimal handling.

For future work, we envision enhancing the model's robustness by training it on a more diverse and balanced dataset, incorporating individuals from various countries, ethnicities, and age groups. Additionally, we propose exploring Federated Learning to train a model on non-public image data, ensuring privacy and security while expanding the model's reach.

We believe that our research can assist both businesses and governmental organizations while also raising awareness among individuals regarding the importance of BMI and its impact on health. This can empower people to take proactive measures to monitor and maintain a healthy BMI.

References

1. SingleCare Team, "Overweight and obesity statistics 2021," singlecare.com, Jan. 21, 2021. Available: https://www.singlecare.com/blog/news/obesity-statistics/. [Accessed Aug.].
2. Lingyun Wen, Guodong Guo, "A computational approach to body mass index prediction from face images," Image and Vision Computing, Volume 31, Issue 5, 2013, Pages 392-400, ISSN 0262-8856.
3. M. Barr, G. Guo, S. Colby, M. Olfert, Detecting body mass index from a facial photograph in lifestyle intervention, Technologies 6 (3) (2018) 83.
4. E. Kocabey, M. Camurcu, F. Ofli, Y. Aytar, J. Marin, A. Torralba, I. Weber, "Face-to-BMI: Using Computer Vision to infer Body Mass Index on Social Media," Proceedings of the International AAAI Conference on Web and Social Media (ICWSM), pp. 572-575, 2017.
5. R. Bhallamudi et al., "Deep Learning Model for Resolution Enhancement of Biomedical Images for Biometrics," in Generative Artificial Intelligence for Biomedical and Smart Health Informatics, Wiley Online Library, pp. 321–341, 2025.
6. R. Bhallamudi et al., "Artificial Intelligence Probabilities Scheme for Disease Prevention Data Set Construction in Intelligent Smart Healthcare Scenario," SLAS Technology, vol. 29, pp. 2472–6303, 2024, Elsevier.
7. R. Bhallamudi, "Improved Selection Method for Evolutionary Artificial Neural Network Design," Pakistan Heart Journal, vol. 56, pp. 985–992, 2023.
8. R. Bhallamudi et al., "Time and Statistical Complexity of Proposed Evolutionary Algorithm in Artificial Neural Networks," Pakistan Heart Journal, vol. 56, pp. 1014–1019, 2023.
9. R. Krishna et al., "Smart Governance in Public Agencies Using Big Data," The International Journal of Analytical and Experimental Modal Analysis (IJAEMA), vol. 7, pp. 1082–1095, 2020.
10. N. M. Krishna, "Object Detection and Tracking Using YOLO," in 3rd International Conference on Inventive Research in Computing Applications (ICIRCA-2021), IEEE, Sept. 2021, ISBN: 978-0-7381-4627-0.
11. N. M. Krishna, "Deep Learning Convolutional Neural Network (CNN) with Gaussian Mixture Model for Predicting Pancreatic Cancer," Springer US, vol. 1380-7501, pp. 1–15, Feb. 2019.
12. N. M. Krishna, "Emotion Recognition Using Skew Gaussian Mixture Model for Brain–Computer Interaction," in SCDA-2018, Textbook Chapter, ISBN: 978-981-13-0514, pp. 297–305, Springer, 2018.
13. N. M. Krishna, "A Novel Approach for Effective Emotion Recognition Using Double Truncated Gaussian Mixture Model and EEG," I.J. Intelligent Systems and Applications, vol. 6, pp. 33–42, 2017.
14. N. M. Krishna, "Object Detection and Tracking Using YOLO," in 3rd International Conference on Inventive Research in Computing Applications (ICIRCA-2021), IEEE, Sept. 2021, ISBN: 978-0-7381-4627-0.
15. T. S. L. Prasad, K. B. Manikandan, and J. Vinoj, "Shielding NLP Systems: An In-depth Survey on Advanced AI Techniques for Adversarial Attack Detection in Cyber Security," in 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS), IEEE, 2024.
16. S. Sowjanya et al., "Bioacoustics Signal Authentication for E-Medical Records Using Blockchain," in 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), vol. 1, IEEE, 2024.
17. N. V. N. Sowjanya, G. Swetha, and T. S. L. Prasad, "AI Based Improved Vehicle Detection and Classification in Patterns Using Deep Learning," in Disruptive Technologies in Computing and Communication Systems: Proceedings of the 1st International Conference on Disruptive Technologies in Computing and Communication Systems, CRC Press, 2024.
18. C. V. P. Krishna and T. S. L. Prasad, "Weapon Detection Using Deep Learning," Journal of Optoelectronics Laser, vol. 41, no. 7, pp. 557–567, 2022.
19. T. S. L. Prasad et al., "Deep Learning Based Crowd Counting Using Image and Video," 2024.
20. Geometric Morphometric Image Analysis. PLoS ONE 12(1): e0169336. doi:10.1371/journal.pone.0169336.
21. Jiang, Min & Shang, Yuanyuan & Guo, Guodong. (2019). On Visual BMI Analysis from Facial Images. Image and Vision Computing. 89. 10.1016/j.imavis.2019.07.003.
22. H. Siddiqui, A. Rattani, D. R. Kisku and T. Dean, "AI-based BMI Inference from Facial Images: An Application to Weight Monitoring," 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA), 2020, pp. 1101-1105, doi: 10.1109/ICMLA51294.2020.00177.
23. A. Dantcheva, P. Bilinski, F. Bremond, "Show me your face and I will tell you your height, weight and body mass index," Proc. of 24th IAPR International Conference on Pattern Recognition (ICPR), (Beijing, China), August 2018.

24. Ashok, N., Prasadarao, K., Judgi, T. (2023). Evaluation of Security of Cloud Deployment Models in Electronic Health Records. In: Jeena Jacob, I., Kolandapalayam Shanmugam, S., Izonin, I. (eds) Expert Clouds and Applications. ICOECA 2022. Lecture Notes in Networks and Systems, vol 673. Springer, Singapore. https://doi.org/10.1007/978-981-99-1745-7_10
25. Karras, Tero & Laine, Samuli & Aila, Timo. (2019). A Style-Based Generator Architecture for Generative Adversarial Networks. 4396-4405. 10.1109CVPR.2019.00453.
26. Davis E. King. Dlib-ml: A Machine Learning Toolkit. Journal of Machine Learning Research 10, pp. 1755-1758, 2009.
27. Szegedy, Christian & Vanhoucke, Vincent & Ioffe, Sergey & Shlens, Jon & Wojna, ZB. (2016). Rethinking the Inception Architecture for Computer Vision. 10.1109/CVPR.2016.308.
28. Parkhi, O. M., et al. 2015. Deep face recognition. In British Machine Vision Conference.
29. Cao, Qiong & Shen, Li & Xie, Weidi & Parkhi, Omkar & Zisserman, Andrew. (2018). VGGFace2: A Dataset for Recognising Faces across Pose and Age. 67-74. 10.1109/FG.2018.00020.
30. K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” CoRR, vol. abs/1409.1556, 2014.
31. F. Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions,” In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, pp. 1251-1258, 2017.
32. Lin, Min & Chen, Qiang & Yan, Shuicheng. (2014). Network In Network. 10.
33. N. Ashok and T. Judgi, "Advanced Techniques in Dynamic Key Management and Multilayered Security for Securing Cloud Infrastructures Using Key-Aggregate Encryption Method," 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), Bengaluru, India, 2024, pp. 1290-1295, doi: 10.1109/ICICNIS64247.2024.10823242.
34. Srivastava, Nitish & Hinton, Geoffrey & Krizhevsky, Alex & Sutskever, Ilya & Salakhutdinov, Ruslan. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Journal of Machine Learning Research.
35. 15. 1929-1958.
36. Hendrycks, D., Gimpel, K.: Bridging nonlinearities and stochastic regularizers with gaussian error linear units. CoRR abs/1606.08415 (2016).
37. Kingma, Diederik & Ba, Jimmy. (2014). Adam: A Method for Stochastic Optimization. International Conference on Learning Representations.
38. Howard, Jeremy & Ruder, Sebastian. (2018). Universal Language Model Fine-tuning for Text Classification. 328-339. 10.18653/v1/P18-1031.
39. Jin, Xiaojie & Chen, Yunpeng & Dong, Jian & Feng, Jiashi & Yan, Shuicheng. (2016). Collaborative Layer-Wise Discriminative Learning in Deep Neural Networks. 9911. 10.1007/978-3-319-46478-7_45.
40. David J. Fisher. (2019, December). Illinois DOC labeled faces dataset, Version 1. Retrieved March 28, 2021 from https://www.kaggle.com/davidjfisher/illinois-doc-labeled-faces-dataset.
41. Domestic Violence Database, “National Violent Offender & Domestic Violence Registry” domesticviolencedatabase.net. Available: https://domesticviolencedatabase.net/registry_ia/?co=Polk&abc=R#abc. [Accessed August. 12, 2020].