IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

ChronoDetect: Predicting Age with Machine Learning

Aditya Singh, Sahibpreet Singh, Yuvraj, Partik and Dr. Raghav Mehra

Computer Science and Engineering

Chandigarh University Mohali, India

Abstract**—** Accurate age detection has emerged as a useful tool in a constantly growing digital environment, spanning sectors including identity verification, wellness, healthcare, and personalized services. Conventional age estimation techniques use static inputs, but new opportunities for data-driven, real-time estimation have been made possible by developments in machine learning and predictive analytics. By utilizing deep learning models with real-time processing, we aim to create a robust system that adapts to diverse datasets and varying environmental conditions. The proposed framework employs optimization techniques to enhance efficiency of the model, ensuring seamless integration into cloud-based platforms for scalable deployment. The proposed study also indulges in deployment of the age detection model as a Software-as-a-Service for various security-based applications, such as security in net-banking. Beyond technical implementation, this study addresses the ethical considerations surrounding age detection, emphasizing fairness, transparency, and data privacy. The results of this research contribute to the growing field of machine learning-driven security applications, providing more insights, and secure identity verification. Through this work, ChronoDetect aims to demonstrate how AI-driven age estimation can be both efficient and ethically responsible, paving the way for broader applications in digital security domains.

Keywords *— Machine Learning, Predictive Analytics, Age Detection, Cloud Computing, Software-as-a-Service (SaaS), Net-Banking, Optimization Techniques, Real-time Processing, OpenCV, TensorFlow.*

I. INTRODUCTION

This paper dives into a fascinating case study focused on creating ChronoDetect, an age classification model that leverages machine learning and data cleansing techniques. The goal of this project is to provide an engaging yet accurate estimate of a person’s age using advanced machine learning frameworks, including OpenCV, TensorFlow, NumPy, and Pandas.

During the development phase, we gathered and processed relevant datasets to boost the accuracy of age predictions. We also integrated real-time processing capabilities to enhance the model's precision in estimating ages. A variety of modification techniques and the most effective algorithms from the machine learning realm were utilized to improve the model’s performance.

In this phase, we really honed in on finding the right decade datasets and technologies for estimating age. Along the way, we encountered some challenges, like refining our datasets, optimizing for real-time use, and managing computational resources for controlled predictions. To tackle these issues, we focused on improving data quality, enhancing our algorithms, and developing better methods for handling data.

This paper dives into the key challenges that impacted the project's technology, the design solutions we implemented, and potential improvements for the system. ChronoDetect is a prime example of how various systems and processes can come together to create an innovative AI-based age estimation tool that sets a new standard in machine learning-assisted biometric analysis.

The system was crafted to be adaptable and scalable, which boosts efficiency when working with larger datasets and enhances classification accuracy. To strengthen its robustness, we explored transfer learning models, allowing our model to leverage networks trained on other datasets, which significantly enhances both accuracy and generalization.

The study also examined the transition from lighter models with fewer parameters to the more complex, well-known models like ResNet and VGG16. By comparing different neural network architectures, we drew some conclusions about how depth and complexity in a model can influence its predictive accuracy. Additionally, we employed techniques like hyperparameter tuning and ensemble methods to maximize accuracy as much as possible.

This paper explains the technical approach, the challenges encountered in designs and solutions undertaken as well as recommendations for improvement. ChronoDetect illustrates the integration of various technologies to design a novel AI-powered tool that provides accurate age estimation thereby improving machine learning based biometric analysis. The next step is to add real-time age estimation for use in some security authentication, digital identity verification, and personalized content recommendation services.

II. LITERATURE SURVEY

Vila-Blanco et al. [1] focus on estimating the chronological age of a subject from the orthopantomogram (OPG) using deep neural networks. The authors use modern imaging techniques by building a convolutional neural network (CNN) that predicts a person’s age from dental x-rays. The paper highlights the processes of feature extraction as well as model training, showing how much better deep learning models perform in age estimation compared to conventional methods which rely on statistics.

Hassan et al. [2] present a deep learning architecture that estimates a subject’s age and sex from optical coherence tomography (OCT) scans. Their study taps into the capabilities of OCT imaging and artificial intelligence to derive substantial biometric information. The authors report training a convolutional neural network (CNN) on a considerable amount of OCT scans and achieved great accuracy in both age and gender classification. The research emphasizes the effectiveness of demographic attribute inference through deep learning models using retinal structure images, which has implications for value-based healthcare and the diagnostics of diseases. Limitations of the study include lack of ongoing monitoring with other groups and improved generalizability.

Zhu et al. [3] analyzes the benefit of using several feature extraction techniques for more accurate age estimation. Their study is focused on the combination of local binary patterns, histogram-oriented gradients, and deep learning feature representations. The authors obtained better prediction performance by using a combination of all the methods than using individual feature extraction techniques.

Abirami et al. [4] delve into methods of age estimation using facial images and provide a broad overview of everything they have come across. They span between various machine learning approaches, and deep learning architectures like CNNs and GANs as well as traditional regression models and support vector machines. These authors also elaborate on the difficulties of age estimation caused by non-uniform lighting, differences in the pose of the subject, and facial expression variations that can challenge the models’ performances. The paper additionally notes improvements that have been made recently regarding model transfer learning and data augmentation that make the models more robust. The review, however, shows that despite deep learning models improving the age estimation problem, a lot more work is required to mitigate the biases, and generalization challenges that remain.

Alonso-Fernandez et al. [5] focus on the post-pandemic period and study the facial masks' effects on soft-biometric predictions such as age and gender classification. The study seeks to understand in what ways more recent CNN-based facial recognition models deal with masked faces. The authors conclude that even though facial masks hide some key features of the face, age prediction is still possible using deep learning models specifically trained with masked datasets.

Antipov et al. [6] examine the most effective training approaches for CNNs focused on age and gender estimation. Their work shows that large scale datasets, data augmentation, and transfer learning are critical for the optimization of deep learning models for demographic studies. The authors seek to ascertain those CNN designs that would provide the greatest accuracy per cost ratio by comparing several CNN systems. The work highlights the need for strong model training practices, especially when there is small, labeled datasets to work with. Some of the potential uses for this work include advertising, security, and content targeting by age groups.

Haseena et al. [7] focus on designing an age and gender estimator model for human face images using artificial intelligence. Their model aims to identify facial features and subdivide people into different age groups through deep learning techniques. This study focuses on using the classification of images with CNNs and attempts to reduce misclassification of complex image data.

Bowgikar et al. [8] discuss a paper regarding predicting the age of an individual by first recognizing their gender through images. The study combines CNN frameworks along with machine learning classifiers to achieve a strong age estimation model. The authors point out that accurately predicting a person's age requires careful consideration of facial landmarks, examination of skin texture, and analysis of bone structure. The study's conclusions suggest that incorporating gender classification before age estimation increases prediction accuracy, since aging affects facial features differently across sexes.

III. METHODOLOGY

The dataset used by the model contains images of faces belonging to different age groups from 1 year old to 99-year-old, i.e., there are 99 classes in the dataset. The dataset contains about 10000 images. The source of the dataset is from wiki art and the images are extensively cropped to only include faces and then these images are all resized to be in the same size of 256 by 256 pixels. The original dataset mostly does not contain real photo angles and different rotations so these changes have been applied manually in the code by using a function. The faces also exhibit a variety of natural facial expressions.

The labels are adjusted from 99 labels for each age to 4 labels belonging to the following age groups:

- Ages 0-25
- Ages 26-50
- Ages 51-75
- Ages 76-100

The images are then loaded into three different models which are:

- Simple CNN model consisting of an input layer, 2 sets of Conv2D + MaxPooling2D layers and at last the outputs from the Convolutional layers are flattened and then sent to the Dense layer consisting of 4 neurons and softmax activation for final output of the model.
- ResNet is utilized through transfer learning, it is a deep neural network which is capable on working on vast image datasets providing accurate results. It utilizes skip connections ,i.e., some connections in the network can be skipped while the model runs. This helps save up time and also pertain better model layers.
- VGG16 is also used through transfer learning and it is also a deep neural network which is capable of getting great results on larger or more complex datasets. It achieved significant accuracy in the image net dataset making it a prominent model in the field of deep learning.

The results from the model training are then evaluated using a confusion matrix and then tested with different images downloaded from the web whether they are being correctly classified or not.

The model will then be integrated with a net banking cross verification system/validation system where the system will ask for an upload from the user while making a transaction, the upload could be video feed or an image given to the system.

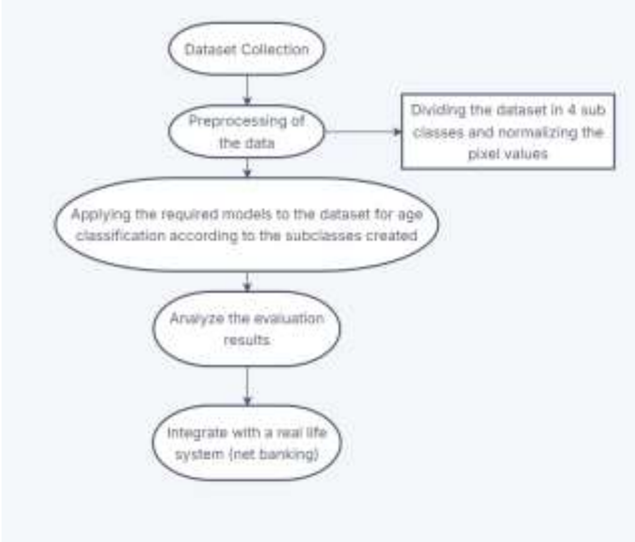

Fig 1. Model Workflow Diagram

An example Simple CNN model framework used by us in the code:

Model: "sequential_6"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 253, 253, 128)	6,272
conv2d_13 (Conv2D)	(None, 251, 251, 64)	73,792
max_pooling2d_8 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_14 (Conv2D)	(None, 60, 60, 32)	18,464
max_pooling2d_9 (MaxPooling2D)	(None, 30, 30, 32)	0
flatten_6 (Flatten)	(None, 28800)	0
dense_6 (Dense)	(None, 4)	115,204

Total params: 641,198 (2.45 MB)

Trainable params: 213,732 (834.89 KB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 427,466 (1.63 MB)

Fig 2. Simple CNN Model Architecture

ResNet and VGG16 in Comparison:

Despite being widely used convolutional neural network (CNN) architectures, their performance and design varies greatly.

1. VGG16

   Originally released in 2014, the Classic Feature Extractor VGG16 (Visual Geometry Group 16-layer network) is a deep CNN. Its architecture is straightforward and well-organized:

   - 3x3 convolution layers that are stacked and activated by ReLU.
   - Layers of max pooling to minimize dimensionality.
   - Final layers for categorization that are fully integrated.

   Benefits of VGG16:

   - Its simple design makes it simple to comprehend and use.
   - Performs effectively in a variety of tasks as a feature extractor (transfer learning).
   - Does a respectable job on small to medium-sized datasets.

Drawbacks for VGG16:

- Its size (~528MB), which makes it difficult to train and operate.
- Computationally costly because there are a lot of parameters (around 138 million).
- The vanishing gradient problem, which causes information to be lost in deeper levels, makes very deep structures difficult to use.

2. ResNet: The Revolutionary Skip Connections System

A breakthrough in deep learning was made in 2015 with the introduction of ResNet (Residual Network). To prevent vanishing gradients and improve learning for deeper networks, it incorporated skip connections (residual learning) in place of merely stacking layers.

Benefits of ResNet:

- Uses skip connections to solve the vanishing gradient issue.
- Much more in-depth training is possible (ResNet-50, ResNet-101, ResNet-152).

Drawbacks for ResNet:

- Is computationally costly when employing more complex variants, such as ResNet-101 or ResNet-152.
- Deeper networks may overfit, therefore they are not necessarily the ideal for limited datasets.

Better/Preferred architecture:

- For straightforward assignments and transfer learning: VGG16 (user-friendly, good performance).
- For more accurate deep networks: ResNet (better at handling complicated photos).

IV. OBJECTIVE

The project seeks to accomplish the following goals to address the issues that have been identified in the process.

This study specifically seeks to:

- *Prepare and loading the dataset*

  To find an appropriate dataset for the task of face age recognition and then preprocess the dataset in a way the images are of the same size and the pixel values of the images are also normalized between a range of 1-0. Also apply random transformations to the image if necessary.
- *Prepare the ML model*

  To classify the images, present in the dataset according to the labels that we have defined we first need to create a model that can accurately classify the images which are being given to it. We aim to prepare a simple CNN model using a smaller architecture and then we will compare the results of classification between 2 major models which will be ResNet and VGG16.
- *Evaluating the results*

  To analyze and evaluate the results generated by the model and identify the shortcomings and infer the results from the model. For this task a confusion matrix will be plotted for each model so that we can easily compare different models as well as we can observe that which classes are being correctly or incorrectly being classified by the model.

V. SYSTEM DESIGN

I. Hardware

To run the code a system with at least 16gb of RAM along with a GPU (Nvidia 2060 or above) is highly recommended. If the same specification is not available with the user, they can utilize cloud platforms and their virtual instances for running the same code.

II. *Software*

No specific software is needed for running the ML models any code editor capable of running python and supporting libraries like TensorFlow will be able to run the program with ease. By integrating the model with the cloud, the model can act as a SAAS or can be used as third-party application.

VI. RESULT ANALYSIS AND VALIDATION

I. *Result Analysis*

For the project and model training purpose, the dataset has been divided into 4 classes which are 0-25, 26-50, 51-75 and 76-100.

The Simple CNN model achieves an accuracy of 59% correctly classifying most images in the 0-25 age group as the dataset has maximum images in the same age group.

Fig 3. Example Images in The Dataset

Fig 4. Testing Image: Predicted class: 0-25 (correct)

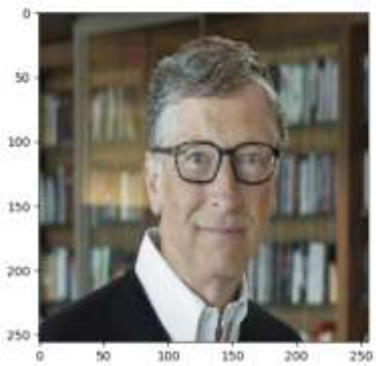

Fig 5. Testing Image 2: Predicted class: 76-100 (incorrect, real age: 69-70 which is close)

Confusion matrix of simple CNN model along with the classification report:

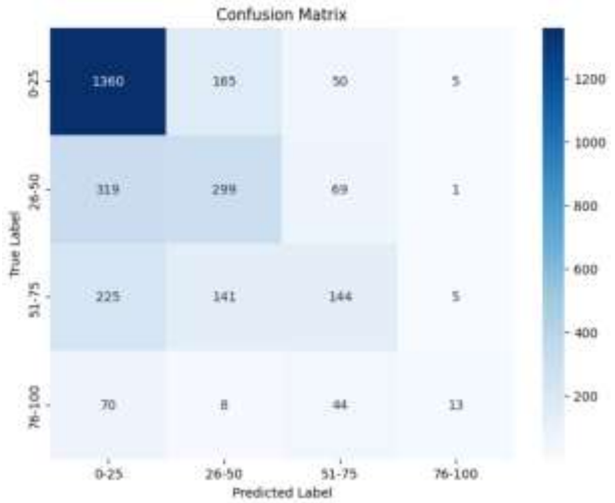

Fig 6. Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
0-25	0.69	0.86	0.77	1580
26-50	0.49	0.43	0.46	688
51-75	0.47	0.28	0.35	515
76-100	0.54	0.10	0.16	135
accuracy			0.62	2918
macro avg	0.55	0.42	0.43	2918
weighted avg	0.60	0.62	0.59	2918

Fig 7. Classification Report

Classification report presents us with the following metrics and their course for the task of facial detection using the CNN model: Precision (0.69), Recall (0.86), and F1-Score (0.77).

VII. LIMITATIONS AND CONSTRAINTS

The model experienced some major problems and limitations during the training process:

1. *Lack of processing/computation problems:*

   The time taken to train the model is very much dependent on the computing power made available to the system that is being utilized to run the program. A GPU with many CUDA cores as well as a higher memory is essential for better training efficiency in terms of training time.

2. *Cost of hardware:*

   Generally better ram with higher speeds as well as GPUs/CPUs with better memory and computation powers are very costly and harder to be accommodated by the average person for a project they just want to simply run for one time.

3. *Availability of dataset:*

   A dataset containing equal number of images in all different age groups is needed which may be easier to achieve but when we account for the fact that the data will be increasing in size, we will also need to see to the fact that we can also efficiently train the model with the newer data.

4. *Anomalies based on facial features*

   Features such as race, lighting and gender create more complexity to the already rigorous task of facial age detection. Different genders create different features for the same age groups which needs to be accounted for, lighting may hide some features on the face from showing up in the image which can worsen results and different race groups belonging to the same age class will show a plethora of new features adding to more complexity.

5. *Approximate results:*

Sometimes the results given by the model can be incorrect but the actual target may be very close to the predicted target. This must also be accounted for to make a better model.

VIII. CONCLUSION AND FUTURE WORK

I. *Conclusion*

In this project, we tackled the challenge of estimating age from facial images by grouping 99 individual age classes into four broader categories. We experimented with three different approaches—a straightforward CNN, as well as more advanced ResNet and VGG16 models through transfer learning.

With only a few convolutional and pooling layers prior to a fully connected output layer, our basic CNN model was able to get an accuracy of roughly 59%. Because there were more photos in our dataset for the 0–25 age range, this result was very strong in that group.

It demonstrates that significant patterns can be extracted from real-world data using even a comparatively basic model, albeit much more can be done. The performance disparity implies that accuracy across all age groups could be improved by more balanced data or additional model adjustment. Furthermore, using transfer learning to integrate complex architectures like ResNet and VGG16 could yield more reliable features, which could result in improved overall results.

II. *Future Work*

The project shows a fair result in predicting user's age from their image and has shown its potential to be integrated with other applications as a third-party application. Some future works and extensions by utilizing this project are listed as below:

1. Utilizing this project or similar CNN models to detect the ages of people trying to access content which is age restricted.
2. CCTV to identify ages of different people trying to access some facility or building which is meant to be accessed by a certain age group only.
3. Automating detection of whether the uploaded photo on identification cards is updated according to the mentioned date of birth or not.
4. Smart systems to identify whether real faces from fake faces to check for tampered or false faces.
5. Integration with audio or biometric scanners, for more accurate age prediction. Further could be used for identification for government applications.

REFERENCES

[1] N. Vila-Blanco, M. J. Carreira, P. Varas-Quintana, C. Balsa-Castro, and I. Tomás, "Deep Neural Networks for Chronological Age Estimation from OPG Images," IEEE Transactions on Medical Imaging, vol. 39, no. 7, pp. 2374–2384, Jul. 2020, doi: 10.1109/TMI.2020.2968765.

[2] O. N. Hassan, M. J. Menten, H. Bogunovic, U. Schmidt-Erfurth, A. Lotery, and D. Rueckert, "Deep Learning Prediction of Age and Sex from Optical Coherence Tomography," IEEE Transactions on Medical Imaging, vol. 40, no. 11, pp. 3073–3082, Nov. 2021, doi: 10.1109/TMI.2021.3074060.

[3] Y. Zhu, Y. Li, G. Mu, and G. Guo, "A Study on Feature Combination for Age Estimation," Proceedings of the IEEE International Conference on Computer Vision (ICCV) Workshops, Dec. 2015, pp. 89-96.

[4] B. Abirami, T. S. Subashini, and V. Maha Vaishnavi, "A comprehensive review on age estimation using facial images," Materials Today: Proceedings, vol. 33, pp. 4706–4711, 2020, doi: 10.1016/j.matpr.2020.05.471.

[5] F. Alonso-Fernandez, K. Hernandez-Diaz, S. Ramis, F. J. Perales, and J. Bigun, "Facial Masks and Soft-Biometrics: Leveraging Face Recognition CNNs for Age and Gender Prediction on Mobile Ocular Images," IET Biometrics, vol. 10, no. 2, pp. 164–180, Jun. 2021, doi: 10.1049/bme2.12046.

[6] G. Antipov, M. Baccouche, S.-A. Berrani, and J.-L. Dugelay, "Effective Training of Convolutional Neural Networks for Face-Based Gender and Age Prediction," Pattern Recognition, vol. 72, pp. 15–26, Dec. 2017, doi: 10.1016/j.patcog.2017.06.031.

[7] S. Haseena, S. Saroja, R. Madavan, A. Karthick, B. Pant, and M. Kifetew, "Prediction of the Age and Gender Based on Human Face Images Based on Deep Learning Algorithm," Computational and Mathematical Methods in Medicine, vol. 2022, Article ID 1413597, Aug. 2022, doi:

10.1155/2022/1413597.
[8] V. Bowgikar, A. V. K. S. Keerthan, B. Shyamsunder, and S. S. Kumar, "Human Age Prediction Based on Gender Image Recognition," Proceedings of the 2022 International Conference on Electronics and Renewable Systems (ICEARS), pp. 1–6, Mar. 2022, doi: 10.1109/ICEARS53579.2022.9752221.
[9] A. Ghildiyal, S. Sharma, I. Verma, and U. Marhatta, "Age and Gender Predictions Using Artificial Intelligence Algorithm," Proceedings of the 2020 International Conference on Intelligent Sustainable Systems (ICISS), pp. 371–376, Dec. 2020, doi: 10.1109/ICISS49785.2020.9316053.
[10] S. Chen, C. Zhang, M. Dong, J. Le, and M. Rao, "Using Ranking-CNN for Age Estimation," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 5183–5192, Jul. 2017, doi: 10.1109/CVPR.2017.550.
[11] C. H. Nga, K.-T. Nguyen, N. C. Tran, and J.-C. Wang, "Transfer Learning for Gender and Age Prediction," Proceedings of the 2020 International Conference on Advanced Technologies for Communications (ATC), pp. 85–90, Oct. 2020, doi: 10.1109/ATC50776.2020.9258347.
[12] V. Sheoran, S. Joshi, and T. R. Bhayani, "Age and Gender Prediction Using Deep CNNs and Transfer Learning," in Computer Vision and Image Processing: 5th International Conference, CVIP 2020, Prayagraj, India, December 4–6, 2020, Revised Selected Papers, Part II, S. K. Singh, P. Roy, B. Raman, and P. Nagabhushan, Eds., Communications in Computer and Information Science, vol. 1401, Springer, Singapore, 2021, pp. 293–304, doi: 10.1007/978-981-16-1092-9_25.
[13] M. F. Mustapha, N. M. Mohamad, G. Osman, and S. H. A. Hamid, "Age Group Classification Using Convolutional Neural Network (CNN)," Journal of Physics: Conference Series, vol. 2084, no. 1, p. 012028, 2021, doi: 10.1088/1742-6596/2084/1/012028.