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Identification Of Person With Mask Using Deep Learning

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Abstract
Covid19 Pandemic Infections Are Spread By Breathing Airborne Particles In The Air And Protective Suits, And But Use A Surgical Mask To Fight Infections Is A Good Idea. Prevention Recommendation, According To Medical Experts From Around The World. Furthermore, Both Public And Private Utility Providers Require Customers To Could Use The Facility If Their Properly Wearing A Few Scientific Studies Regarding Mask Detection Including Ai Technology (Ai) & Image Recognition, But At The Other Hand, Have Been Discovered. We Propose Mobile Net Mask, A Multi-Phase Facial Mask Recognition, Haar Cascade Classifier Design For Reducing Serious Transmitting Of Sars-Cov-2, In This Article. For Develop & Validate A Method For Analyzing Faces In Photographs And Video Even With A Face Mask Streams, Two Separate Face Mask Datasets With 1,000 Images Were Used.

Keyword: - Sars, Deep Learning, Artificial Intelligences, Face Mask Prediction.

1.Introduction

Coronavirus Disease Is A Serious Infectious Disease That Is Caused By Acute Respiratory Syndrome. At Present, We All Know That Covid Has Quickly Spread In Many Countries And Is Affecting Many Individuals. To Avoid This Tragedy, A Practical Approach To Prevent The Spread Of Viruses Is Urgently Desired Worldwide. Some Of The Studies Have Found That Wearing A Face Mask Plays An Essential Role In Preventing The Spreading Of Coronavirus. Wearing A Face Mask Can Ensure Interrupt Airborne Virus From Entering Into Respiratory System Of The Person And Also Patient Suspected With Coronavirus Is Been Required To Wear A Face Mask From Prevention Of Virus From Him To A Health Person.

That Efficacy Of A Face Shield In Preventing The Transmission Of Disease Of Virus Has Been Diminished Mostly Due To Improper Wearing Of Facemask. Therefore, We Have Developed An Automatic Detection Approach For Identification Of A Person With A Mask Which Can Contribute To Personal Protection And Public Prevention.

Here The Distinctive Facial Character Of A Person With Mask Will Provide An Opportunity For Figure 1 Images Of Persons Wearing Mask2 Automatic Identification. We Use Deep Learning And Computer Vision Technology For Automatic Identification, The Main Components Deep Learning Methods Are Deep Neural Network Which Have Demonstrated Superior Performance In Many Streams Including Object Detection, Image Calcification, Image Segmentation One Of The Primary Models Of Dnn Is Convolution Neural Network Which Have Been Wide Used In Computer Vision Task. So Here We Basically Used A Haar Cascade Classifier For Accuracy Improvement In Facial Image

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Classification So We Intended To Develop A Method Using A Mobile Net V2 Architecture To Identify Facemask Conditions In Order To Improve Our Accuracy With Low Quality Facial Images.

Our Main Contribution Are Summarized As Follow

1. Develop A Face Identification Method Using Haarcascade Classifier.
2. Utilization Of Deep Learning Methods For Identification Face Mask
3. We Have Used Mobile Net V2 Architecture Including Activation Function Density, Which Outperforms The Probability Percentage To A Person Wearing A Mask.

Figure 1 Images of persons wearing mask

2.Proposed Model

We Used The Mobile Net V2 Architecture, Which Seems To Be A Substantial Advance Over Mobilenetv1 And Advances The Condition On Digital Image Perception, Particularly Detection, Object Identification, And Feature Extraction.23 The Haarcascade Classifier, Which Is An Efficient Supervised Learning Strategy.

It Is Then Used To Identify The Objects In All The Other Images Based On The Training. This Is A Deep Learning-Based Method In Which A Cascade Supervised Learning Method Using A Large Number Of Distinct Images.

3.Related Work

- **Harr Cascade Classifier: -**

  [1] It Is A Classification Technique Based On The Assumption Of Positive And Negative Images And Detecting Faces. [2] The First Move Is To Gather The Haar Characteristics. A Haar Function Is A Collection Of Calculations Performed On Adjacent Rectangular Regions In A Detection Window At A Particular Location. The Estimation Entails Adding Up The Pixel Intensities In Each Area And Then Subtracting The Sums. [3]

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Applications Of Harr Cascade:1. Facial Recognition: Similar To How The Iphone X Uses Facial Recognition For Safe Login, Other Electronic Devices And Security Protocols May Use Haar Cascades To Assess The User's Validity. 2. Robotics: Using Object Recognition, Robots Can "Sense" Their Surroundings And Perform Tasks. This Could Be Used To Simplify Production Processes, For Example. 3. Autonomous Vehicles: Autonomous Vehicles Need Awareness Of Their Environment, And Haar Cascades Can Aid In The Identification Of Objects Such As Pedestrians, Traffic Lights, And Sidewalks, Allowing For Better Decisions And Increased Protection.

- **Mobile Net V2**: -

[4] There Are Two Kinds Of Blocks In Mobilenetv2. The First Is A Relicblock With A Stride Of Another Choice For Downsizing Is A Block With A Stride Of Two. Both Forms Of Blocks Have Three Layers. [5] The First Layer Is 11 Convolution With Relu6 This Time. The Depthwise Convolution Is The Second Sheet. Another 11 Convolution Is Used In The Third Layer, But This Time There Is No Non-Linearity. If Relu Is Used Again, Deep Networks Can Only Have The Power Of A Linear Classifier On The Non-Zero Volume Portion Of The Output Domain, According To The Argument. There Is Also A T Expansion Factor. For One Of The Major Experiments, T=6 Was Used. The Internal Output Would Have 64t=646=384 Channels If The Data Had 64 Channels.Where T Is The Expansion Factor, C Is The Number Of Output Channels, N Is The Number Of Repetitions, And S Is The Stride. For Spatial Convolution, 33 Kernels Are Used.The Main Network (Width Multiplier 1, 224224) Uses 3.4 Million Parameters And Has A Computing Cost Of 300 Million Multiply-Adds. (In Mobilenetv1, The Width Multiplier Is Introduced.)For Input Resolutions Ranging From 96 To 224 And Width Multipliers Ranging From 0.35 To 1.4, The Output Trade-Offs Are Further Investigated. [6] The Network Computation Takes Up To 585 Million Madds, And The Model Scale Ranges From 1.7 Million To 6.9 Million Parameters.To Train The Network, 16 Gpus Are Used With A Batch Size Of 96. [7] The Mobilenetv2 Architecture Is Built On An Inverted Residual Configuration, Where The Residual Block's Input And Output Are Thin Bottleneck Layers. Unlike Standard Residual Models, Which Use Extended Representations In The Input, Mobilenetv2 Filters. Features In The Intermediate Expansion Layer Using Lightweight Depth Wise Convolutions. [8] In Order To Preserve Representational Strength, We Have Discovered That Non-Linearities In The Narrow Layers Must Be Removed. We See How This Enhances Efficiency And Discuss The Inspiration For This Concept Finally, Our Method Decouples The Input/Output Realms From The Transformation's Expressiveness, Providing A Useful Context For Further Investigation. Image Net Classification, Coco Object Recognition, And Voc Image Segmentation Are Used To Evaluate Our Results. We Compare The Precision, The Number Of Operations Determined By Multiply-Adds (Madd), And The Number Of Parameters.

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Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Figure 2 Mobile net v2 architecture process

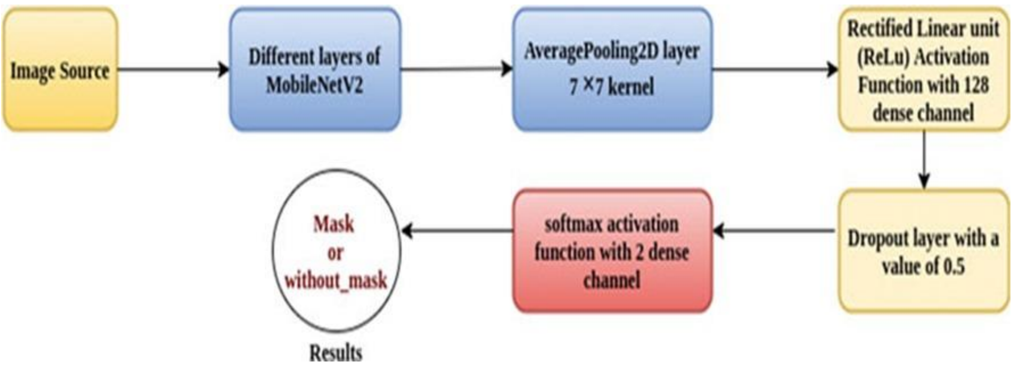

Figure3 Mobile net v2 architecture

4.Visualization Of The Datasets

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We Have Collected Dataset Manually With Mask And Without Mask, We Have Also Taken Data From Kaggle Website Where We Don't Have Any Copyrights.

Figure 4 Without mask

Figure 5 With Mask

5.Output

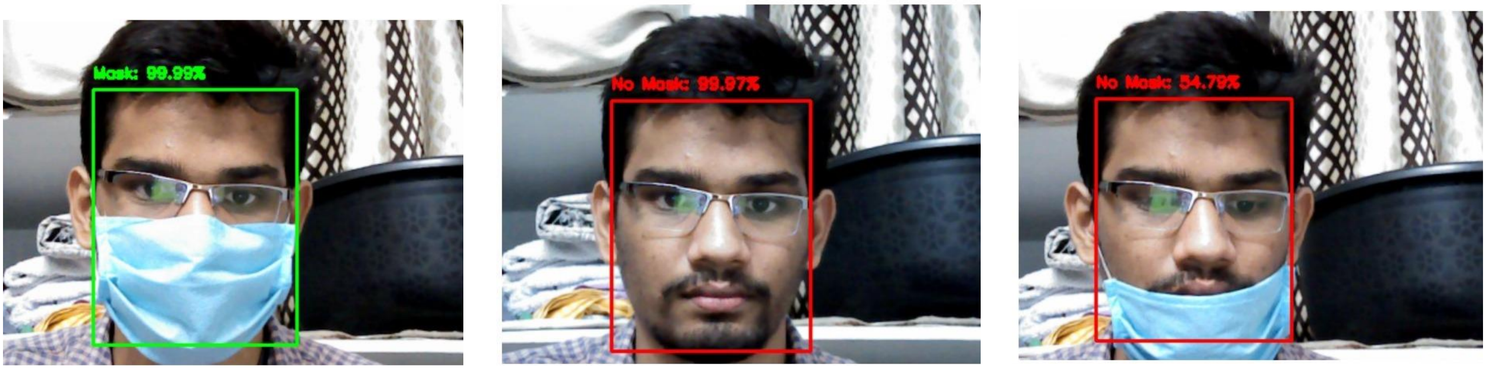

Figure 6 Live Identification of Face mask Images

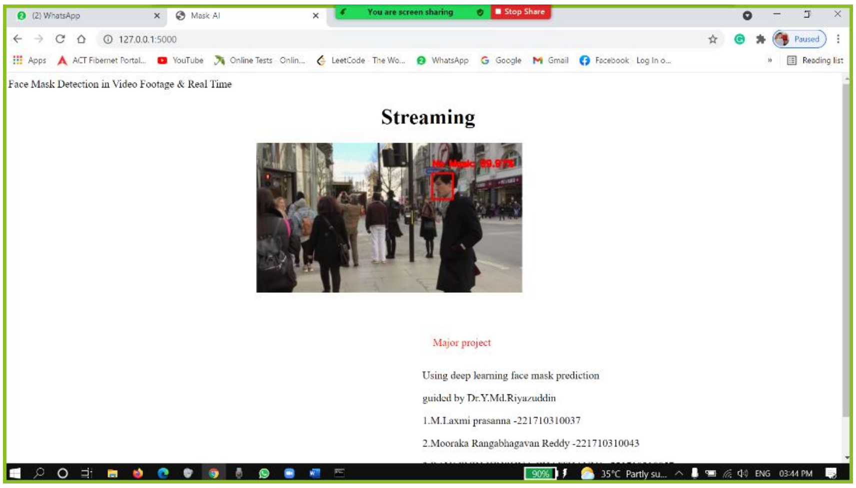

Figure 7 Video no mask output (99.97%)

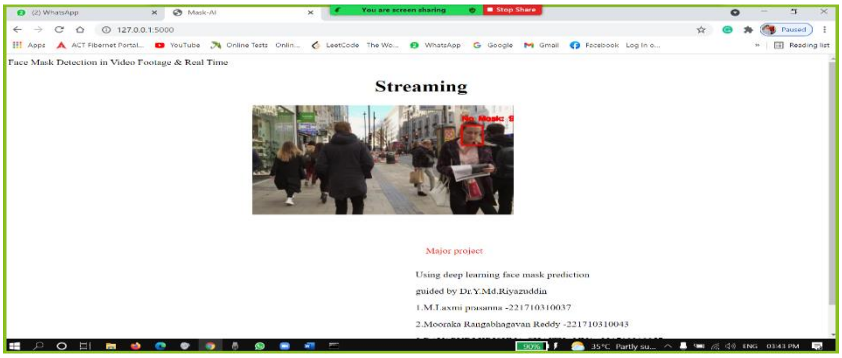

Figure 8 Video no mask output (98%)

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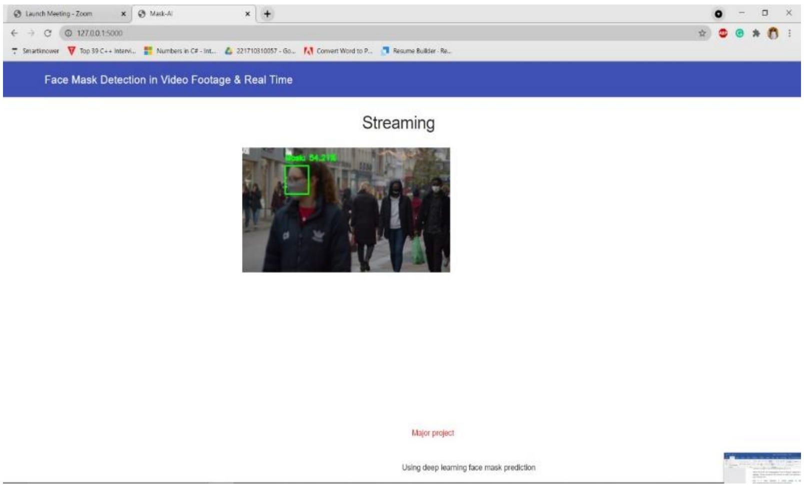
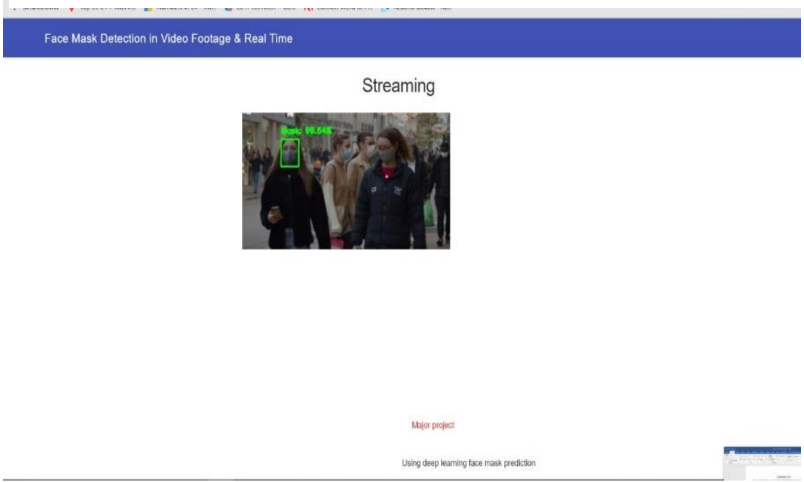


Figure 9 Video with mask output (94.21%)

Figure 10 Video with mask output (94.21%)



6.Conclusion

In This Project, We Developed A Face Mask Detector Which Is Used To Identify Whether The Person Is Wearing Mask Or Not.

Firstly, We Detected Face Using Haar Cascaded Classifier In This Haar Cascaded We Will Have Different Facial Regions For Our Project We Used Frontal Face Haar Cascaded Classifier Images.

Haar Cascaded Classifier Is The Best Classifier In Detecting Faces.

Next We Detecting Face Mask Of Person Using Mobile Net V2 Architecture This Architecture Identifies The Features Well.

We Have Live Detected The Outputs And Identified Whether The Person Is Wearing A Face Mask Or Not.

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We Have Also Calculated The Probability Of Person With And Without Mask And We Even Detected The Face Mask Through Video Streams. In Both The Cases, We Have Got Result And Our Project Can Be Used In Many Public And Private Sectors.

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