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CNN based Covid-aid: Covid 19 Detection using Chest X-ray

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***Abstract*—Covid-19, an infectious disease that first originated from Wuhan, a city in China, during the month of December 2019, has taken a toll on the everyday lives of people around the world by affecting their mental and physical health. In addition to being detrimental to public health, it has also shaken the global economy. With the rapid spreading rate of this virus, one must find an effective and expeditious method to detect the disease. Radiology is one field of medical science that helps to diagnose patients carrying coronavirus symptoms. With inspiration and insight from various papers, this study aims to carry out the task of detecting the disease through radiography images of the human chest. Our deep learning model works on a publicly available dataset and uses the concepts of convolutional neural networks. Our model generated a classification accuracy of 87%.**

Keywords—Covid-19; Convolutional Neural Networks; Deep learning; Chest X-ray images; Image processing; Pneumonia

I. INTRODUCTION

Globally as of 24th February 2021, there have been around 111,593,583 confirmed cases of Covid-19, including 2,475,020 deaths, reported to WHO; the data shows that the United States has the maximum number of cases followed by India, Brazil, the Russian Federation, and many others [1]. The very onset of Covid-19 began from Wuhan, Hubei Province of China on 31st December 2019 when people started to report mysterious cases of Pneumonia with unknown causes. Since then, it has transformed into a pandemic [2-4]. Many government institutions across the world have implemented lockdowns, travel restrictions, and the most common measure of social distancing as a way to protect its citizens, residents, and tourists. However, they failed to realize the psychological health impact it would have on many people. In a recent study by Chaturvedi et al., 51.4% of the survey participants responded that they were not productive during the lockdown and suffered from poor mental and physical health symptoms [5]. With rising cases world-wide, the most commonly occurring symptoms of Covid-19 are fever and cough. Covid-19 has a significantly high incubation period of about 13 days. Some patients even tend to remain relatively asymptomatic with a minor headache. Both the combination of high incubation period and asymptomatic cases, make it a tedious task to detect, trace, and contain the virus. In addition to this, pneumonia is one of those respiratory diseases which has a high tendency to affect the lungs of human beings, in particular [6-8]. In a normal scenario, whenever someone breathes air, the alveoli present in the lungs are filled with oxygen. However, in the case of a person infected with pneumonia, the alveoli are filled with blood and pus. This can be very uncomfortable for anyone and they may also develop symptoms such as fever, tiredness, and have trouble breathing [9, 10]. Both these diseases have similar symptoms and detecting them can be a tedious task. Therefore, it is of utmost importance that the detection of the SARS-CoV-2 virus is done accurately.

The most widely used method to test Covid-19 disease is the RT-PCR test which is short for a real-time reverse transcription-polymerase chain reaction. This method is usually time-taking as the process of taking the test along with transporting samples takes more than half a day. The average turnaround time for this type of test is 3-6 days [11]. On the other hand, CT scans and X-rays also help in the detection of this disease in a short period. There is a major advantage of using X-Ray image detection over CT Scans as it is cost-effective, especially for under-developed and developing nations, where resources are scarce [12]. There have been numerous researches since the beginning of 2020 that focused on generating techniques and models to distinguish people carrying a potential risk to this disease from the healthy ones [13-15]. Most of these aims to classify images of X-Ray or CT Scans as normal or not by employing the concept of convolutional neural networks (CNNs) which helps to identify probable cases of coronavirus. CNN's usually demonstrate high-accuracy results in the area of image and object recognition [16] which is why we used this approach. The success comes from CNN's ability to capture hidden attributes of the image through various hidden layers. With time, CNNs have only evolved. The first one was LeNet-5 [17] which only had 5 layers to it, whereas another CNN known as ResNet-50 [18] has a deep architecture of 152 layers. Out of the many, two of the famous and popularly used models are the ResNet model, short for Residual Network, and the DarkNet model. As the name suggests, ResNet 152 has 152 layers. ResNet was the model that won the ImageNet challenge in 2015; It was mainly used to train extremely deep networks and it solved the problem of deep neural networks which was difficult because of the vanishing gradient problem [19]. Another model is the DarkNet model which is also quite popular. The DarkNet architecture has fewer layers as compared to 152 layered ResNet. It is also a better option because it helps achieve the desired model fitting, which is neither under-fitting nor over-fitting [11].

Deep learning has changed the way we use data and how we perceive artificial intelligence. It is called deep learning because the networks have various layers and a large number of trainable parameters. Here, in our study, we have used a popular neural network called CNN (Convolution neural

network). Another name for this is ConvNet. It mainly helps to process information that has an entire framework of a grid structure, for example, an image. Images are made up of pixels that are arranged in a lattice framework and each grid has a unique value that describes the brightness and color of that pixel. The human brain has the ability to grasp information from images as each neuron works in its receptive field. With a network of many neurons, the brain covers the entire visual field. In a similar fashion, CNNs can process data in their receptive fields [20].

Our work revolves around implementing a novel and unique 19-layered convolutional neural network structure which can determine the detection of Covid-19 disease and differentiate it from pneumonia, using X-ray images. Our model is available at https://github.com/piyushHere/covid-detector.

II. Related Work

Machine learning applications have tremendously stepped-up the game for clinicians around the world by automating medical diagnosis [21-25]. Deep learning, a famous research field in AI technology, helps in automated feature extraction [26, 27]. It has been applied to various detection and classification problems in the medical field, for example, lung segmentation [28, 29], neural disease classification [30], arrhythmia detection [31-33], pneumonia detection [34], etc.

Similarly, the study of radiology images used for Covid-19 detection has gained substantial attention from researchers across the globe. Hemdan et al. studied the performance of seven different CNN models, namely ResNetV2, DenseNet201, InceptionResNetV2, InceptionV3, Xception, VGG19, and MobileNetV2. Out of the seven, DenseNet201 and VGG19 had the accuracy of 90% [35]. Sethy and Behera used a supervised learning model for classification called as Support Vector Machine (SVM). They studied the performance of eleven different pre-trained neural networks, namely AlexNet, Inceptionv3, ResNet101, XceptionNet, DenseNet201, ResNet18, VGG16, Inceptionresnetv2, GoogleNet, ResNet50, and VGG19. The best performing model was ResNet50 with an accuracy score of 95% [36]. Narin et al. also carried out a study in testing three different neural networks, out of which ResNet50 gave best results [37]. In another study by Apostolopoulos and Bessiana, we can clearly compare the performance of five different pre-trained neural networks, out of which VGG19 outperformed the rest with an accuracy score of 98.75 [13]. Wang and Wong proposed another model for Covid-19 detection called as COVID-Net that helped in multi-class classification: Covid-19, viral pneumonia, and normal. Their accuracy score was 92.4% [38]. Ucar and Korkmaz came up with a fine-tuned SqueezeNet model with an accuracy of 98.3% [39]. Ghosal and Tucker used chest X-Ray images to compare covid-positive and normal cases as well. Their accuracy was 92% [40]. Khobahi et al. worked on a novel semi-supervised neural network that consisted of a Task-Based Feature Extraction Network (TFEN) [41]. Abbas et al. presented a Decompose, Transfer, and Compose (DeTraC) where they used CT scans on a ResNet model [14]. Many other authors Gozes et al. [42], Butt et al. [43], Li et al. [44], Shi et al. [45], have also added to this field of research by using CT scans as their dataset. Panwar et al. put forward a VGG-16 model, which is also based on deep learning techniques [46]. Sarker et al. used the DenseNet-121 on the dates of an already trained model [47]. In the paper published by authors, Xu et al. discuss that CT scans of Covid-19 have various characteristics which are different from other forms of lung diseases like Pneumonia. They used 618 CT images and then augmented this data and the accuracy came around 89.7%. The authors of this paper used ResNet as an architecture [48]. Finally, Ozuturk et al. work inspired us to come up with the covid-aid model. Their work revolves around binary as well as multi-class classification. Their proposed DarkCovidNet model consists of 17 convolution layers [49], whereas our architecture consists of 19 convolution layers.

As mentioned earlier, there have been several attempts to detect Covid-19 faster and more accurately, however, there is nothing significant that exists in our best knowledge that performs better than the laboratory testing kits.

III. Materials and Methods

A. Dataset Description

For our dataset, we used two different sources. The first is from Joseph Cohen's GitHub repository [50] from which we took covid-positive X-Ray images. The second source is the ChestX-ray8 database structured by Wang et al. [51] from which we took X-Rays of normal lungs and pneumonia-infected lungs. JP Cohen's database is made from various open sources and is continuously updated. This database had 127 covid-positive images at the time we prepared our dataset. Out of these, 43 were found to be female and 82 were male. For our training purposes, we have taken 600 images, out of which we have decided to take 100 images as Covid-19 (covid-positive), 100 images as Pneumonia, and the rest 400 images as No_findings. Fig. 1. below shows sample images from the database.

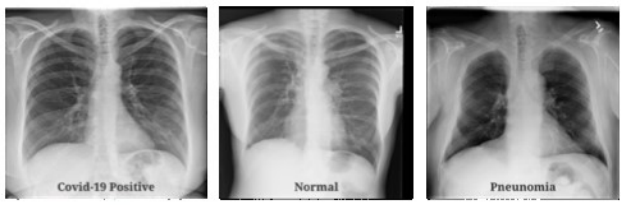


Figure 1. Sample chest X-Ray images used in the model

B. The Covid-Aid Model

Fig. 2. below shows a diagrammatic depiction of the experimental setup for Covid-19 detection.

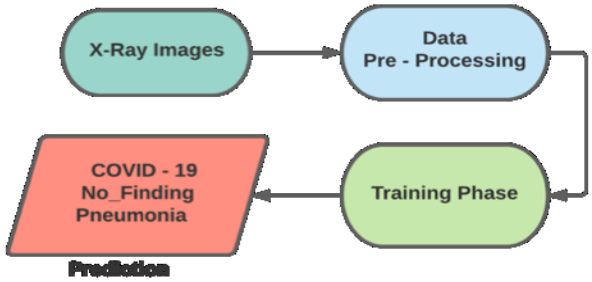


Figure 2. Diagrammatic depiction of experimental setup for Covid-19 detection

Our architecture of the Covid-aid model is inspired by DarkCovidNet's architecture [49]. In our model, there are 19 layers for convolution, (7 are single-layered convolution structures and 4 are triple-layered convolution structures) along with 6 max-pooling layers. The following operations are used in our architecture:

- Each convolution layer of the model is followed by Batch Normalization (BatchNorm) operation, which helps to standardize inputs, stabilize training, speed up convergence and regularize the model [52].
- After Batch Normalization, Leaky rectified Linear Unit (LeakyreLU) operation is applied, which is used to stop neurons from dying [53].
- Maxpool operation, being another important step, is also used as it helps in downsizing the input.

Each convolution block, named as covid-aid block in our model, consists of a convolution layer on which the operations explained above are performed turn by turn. Each triple-layered structure follows this setup thrice. The mathematical convolution operation is explained below:

Convolution is a process of producing a filtered image by passing a kernel, also called a filter, over an image. This filter is moved some distance each time, which is called a stride. We perform the weighted matrix multiplication of this filter on a part of the input image each time before moving this filter along the columns. After reaching the end of each row, we proceed with the next row. After doing this operation along all the rows, we get an output image whose size is given by:

$$((W-K+2P)/S)+1 \qquad (1)$$

where,

W = size of the input image

K = Filter size

S = Stride

P = Padding

Figure 3. Schematic representation of input data through convolution and maxpool layers.

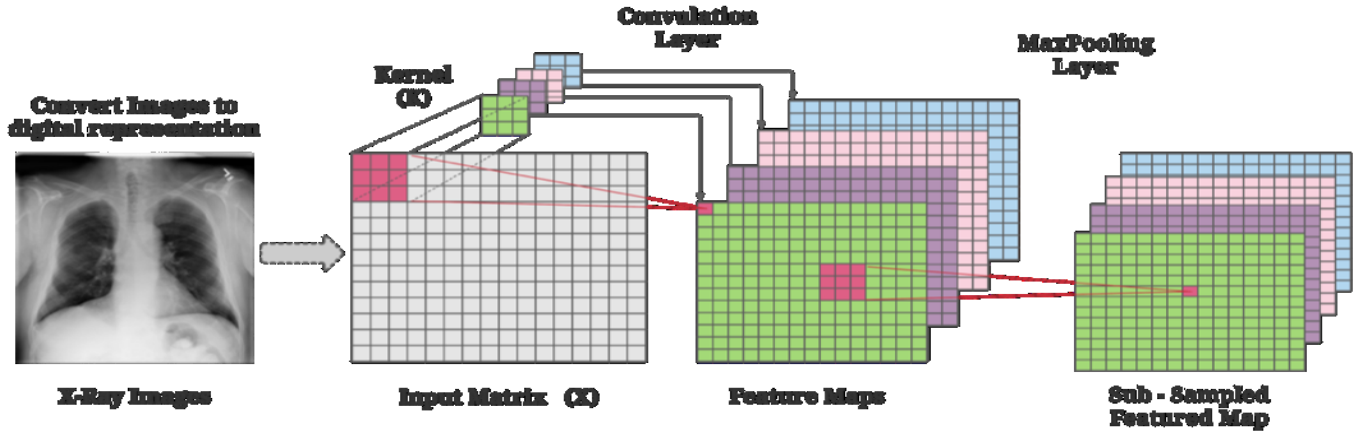
This 2-D convolution can be represented by the following formula:

$$(X * K)(i,j) = \sum_{m} \sum_{n} X(m,n) K(i-m, j-n) \qquad (2)$$

Here, X is the input signal (image), K is kernel and * represents the discrete convolution operation. The filter K slides over the input matrix X with a stride distance S. The convolution operation is then followed by the Leaky ReLu operation. For an input x, the Leaky ReLU operates in the following manner:

$$f(x) = \begin{cases} 0.01x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases} \qquad (3)$$

Fig. 3 shows the movement of input data through various layers. Fig. 4 gives us a better idea of the Covid-aid architecture. In our proposed model, initially, we have a covid-aid block of dimension (3 × 8) since we have three channels incoming for an image. The output of the first covid-aid block is passed through a max-pooling operation that helps in downsizing the inputs. The output from this block enters the next covid- aid block of dimension (8 × 16) with another max-pooling layer. After this, we have 4 triple convolution layers of dimensions (16 × 32), (32 × 64), (64 × 128), and (128 × 256) respectively. Each triple-layer discussed above is followed by a max-pooling layer. The output from the previous layers is then passed onto the next four covid-aid layers of dimensions (256 × 512), (512 × 256), (256 × 128), (128 × 256) respectively. Our final convolution layer is of dimensions (256 × 3). This final layer, which is the Conv_layer, has the ReLU and BatchNorm operation following it. The output obtained is passed through the Flatten layer and then, through a Linear classifier neural network of dimensions (363 × 3). As a result, we get a classifier with three classes at the end of this architecture, which detects Covid-19, No_findings, and Pneumonia. Fig. 5 gives us an idea about the layer details and layer parameters. The total number of parameters in our deep learning model is 1,430,834 as shown in Fig. 6. using the Adam Optimizer [54].



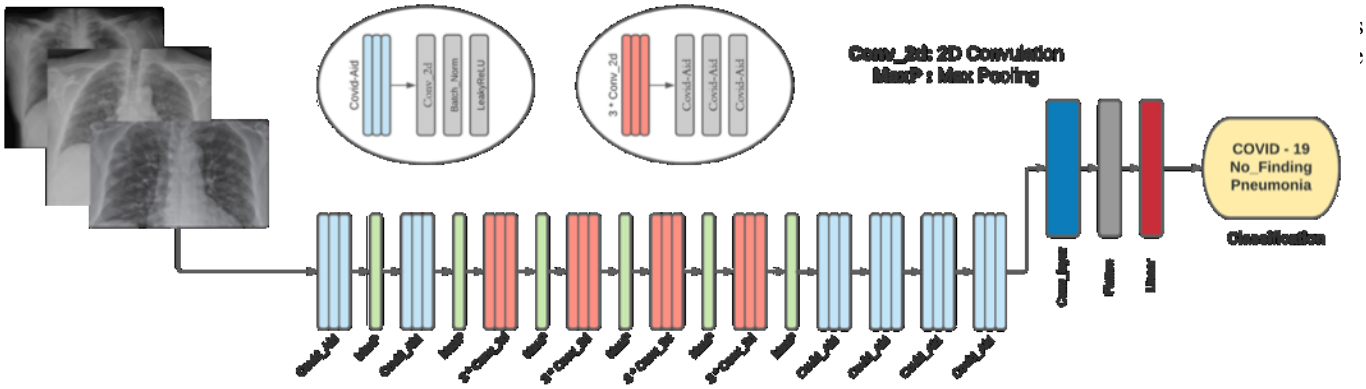


Figure 4. Covid-aid Architecture

Number of Layers	Layer Type	Output Shape	Number of Trainable Parameters
Conv2d	[8,256,256]	216	TRUE
Conv2d	[16,128,128]	1,152	TRUE
Conv2d	[32,64,64]	4,608	TRUE
Conv2d	[16,66,66]	512	TRUE
Conv2d	[32,66,66]	4,608	TRUE
Conv2d	[64,33,33]	18,432	TRUE
Conv2d	[32,35,35]	2,048	TRUE
Conv2d	[64,35,35]	18,432	TRUE
Conv2d	[128,17,17]	73,728	TRUE
Conv2d	[64,19,19]	8,192	TRUE
Conv2d	[128,19,19]	73,728	TRUE
Conv2d	[256,9,9]	2,94,912	TRUE
Conv2d	[128,11,11]	32,768	TRUE
Conv2d	[256,11,11]	2,94,912	TRUE
Conv2d	[512,7,7]	1,31,072	TRUE
Conv2d	[256,9,9]	1,31,072	TRUE
Conv2d	[128,11,11]	32,768	TRUE
Conv2d	[256,11,11]	2,94,912	TRUE
Conv2d	[3,11,11]	6,912	TRUE
Flatten	[363]	0	FALSE
Linear	[3]	1,092	TRUE

Figure 5. Snapshot of layers and background parameters in the model

```
Total params: 1,430,834
Total trainable params: 1,430,834
Total non-trainable params: 0
Optimized with 'torch.optim.adam.Adam', betas=(0.9, 0.99)
Using true weight decay as discussed in https://www.fast.ai/2018/07/02/adam-weight-decay/
Loss function : CrossEntropyLoss
======================================================================
Callbacks functions applied
```

Figure 6. Snapshot of Model Parameter details

C. *Training the Model*

Since training process is a computationally tedious task, it is advised to use a specific hardware like Graphics Processing Unit (GPU) [55]. Once the model was created, it was trained on the dataset as a binary classifier initially, which gave the results as Covid-19 (covid-positive) or No_findings. To train it, we took the batch size as 150 and the learning rate as 3e-3. The number of epochs, which means the number of passes through our dataset, was set to 30. We stepped ahead and added a third class for another respiratory disease to see how well our model behaves at interpreting chest X-Rays. We decided to go ahead with Pneumonia because Covid-19 shows a lot of pneumonia-like symptoms in a lot of patients, so it becomes really important that our model behaves well at distinguishing these two. Thus, we added an equal number of Pneumonia and Covid-19 (covid-positive) images with the rest being in the class labeled as 'No findings' and performed same learning rate of 3e-3. Fig. 7 summarizes the hyper-parameters of our model.

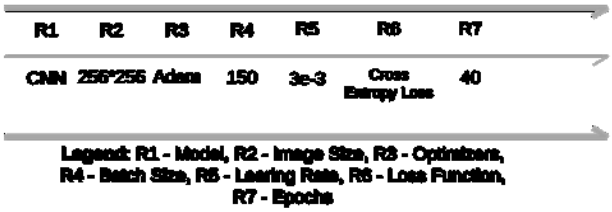


Figure 7. Summary of hyper-parameters of Covid-aid model

IV. RESULTS

We used the Python programming language, Fast AI, which is built on the PyTorch framework; for the general image preprocessing task [56]. In addition to that, a Windows workstation with GeForce GTX 1050 Ti using CUDA, which is an API model for GPU provided by PyTorch library; for experimental work.

A. *Confusion Matrix*

After training the model on the given dataset, we check the efficiency of the model using confusion matrix. This helps us to differentiate the true Covid-19 diagnosed in the X-Ray from the false ones. Confusion matrix explains the output in four categories: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). TP is the number of images that the model predicts correctly as covid-positive labeled whereas, FP predicts images as covid-positive despite them being labeled as non-covid. In a similar way, TN is the value of correctly predicted non-covid images and FN is incorrect prediction of covid-positive images. The outcome is represented in Fig. 8. This figure clearly shows that 17 out of

25, 98 out of 100, and 15 out of 25 images were labeled correctly for Covid-19, No_findings, and Pneumonia class respectively.

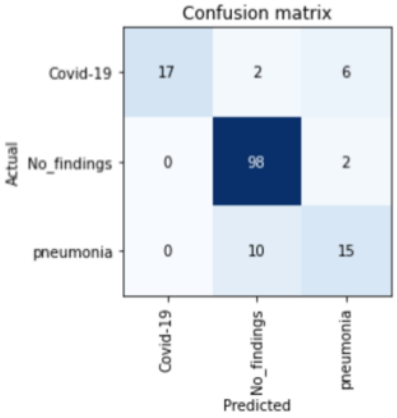


Figure 8. Confusion matrix of test data

B. Performance Metrics

We used the metrics given below to calculate our model's performance effectively:

1) *Accuracy:* This metric is an important criterion for evaluation as it hints us about TP and TN. Accuracy is calculated as the ratio between their summation (TP, TN) and the total values of the confusion matrix. Accuracy value of a model helps to distinguish it from other models and choose the best one for classification purposes. Although, it must be noted that a high value of accuracy is not always preferable as the efficiency of the model depends on other metrics as well.

$$Accuracy = \frac{TP + TN}{Positive + Negative} \quad (4)$$

The Covid-aid model has an accuracy score of 87% as shown in Fig. 9.

2) *Precision:* It represents the ratio between correctly predicted positive images and total number of positive images. A high value of precision means low error rate.

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

The Covid-aid model shows a precision score of 100% for covid-19 positive images, which means that out of all images that labeled as covid-positive, all of them are positive. However, the precision score for pneumonia labeled images is only 65% as shown in Fig. 9.

3) *Recall (Sensitivity):* Recall is the ratio of accurate positive predictions to total predictions. The value lies between 1.00 and 0.00 where the latter is the worst and former is the best value.

$$Sensitivity\ or\ Recall = \frac{TP}{TP + FN} \quad (6)$$

Our model predicts the covid-positive and pneumonia cases with a recall score of 0.68 and 0.60 respectively as shown in Fig. 9. These values are above 0.5 so they can be considered as decent results.

4) *F1-score:* This value is the weighted average of Sensitivity and Precision. It can sometimes help to serve better evaluation results as compared to accuracy, in case of unequal category distribution.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (7)$$

In our model, the covid-positive class yields an f1-score of 0.81 which is comparatively higher than the pneumonia class.

	precision	recall	f1-score	support
Covid-19	1.00	0.68	0.81	25
No_findings	0.89	0.98	0.93	100
Pneumonia	0.65	0.60	0.63	25
accuracy			0.87	150

Figure 9. Snapshot of precision, recall, f1-score, and support values for Covid-19 (covid-positive), No_findings, and Pneumonia classes

It can be noted that the model performs exceptionally well for covid-positive and No_findings classes, but not the same for Pneumonia class. The reason for this could be due to a smaller number of images available in our dataset.

V. Conclusion and Future Work

We implemented a methodology for the detection of the presence of the Covid-19 virus in a human body by processing chest X-Ray images through our Covid- aid model. Our model proved to be 87% accurate in the multi-class classification of the three classes: Covid-19 (covid-positive), Pneumonia, and No_findings. The significant limitation of our study was the unavailability of high quality covid-positive images. Due to this limitation, we had to make use of a large number of trainable parameters. If this weren't the case, then we could have attained better results for a lesser number of epochs, and this could have significantly reduced our training time. On the brighter side, this model can be used effectively in remote places having a shortage of medical experts and/or unavailability of testing kits.

For the future, this deep learning architecture needs to be trained on a wider variety of publicly available dataset so that the performance can yield promising results. In addition to that, it can also help in identifying other chest-related diseases such as Bronchiectasis and SARS. With the help of hospital staff, medical experts, and researchers, we aim to make this model more effective and robust by gathering an ample amount of data for future use. We hope our work inspires others so they may help in improving the accuracy and overall contributing to the community.

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