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3.4.3 DropOut Layer
Dropout is applied to the input.
The Dropout layer, which helps prevent overfitting, randomly sets input units to 0 at a frequency of rate of 0.5 at each step throughout the training period. Inputs that are not set to 0 are scaled up by 1/(1 - rate) such that the sum of all inputs remains constant.
3.4.4 Flattening Operation
The flattening procedure converts the dataset into a 1-D array for input into the fully connected layer, which is the following layer.
3.4.4 Fully Connected Dense layers
The flattening operation's output serves as input for the neural network using ReLu as the activation function. The artificial neural network's goal is to make the convolutional neural network more advanced and capable of identifying pictures. The output layer is constructed using the softMax activation function.
No. of nodes in the Fully connected layer
This is the no. of nodes present in each layer, which is 43 in this case as there are 43 different classes in the dataset.
Activation function, SoftMax
It is employed as the neural network's final activation function to convert the neural network's output to a probability distribution over predicting classes. Softmax's output is in the form of probability for each conceivable result for predicting class. The probability sum for all feasible prediction classes should be one. The equation for softmax is:
σ(z ⃗)i = (e 〖^(z 〖_i〗)〗)/(∑_(j = 1)^K e 〖^(z 〖_j〗)〗)
Where,
σ = Softmax
z ⃗ = Input Vector
e^(z 〖_i〗) = Standard exponential function for input vector
K = No. of classes in the multi-class classifier
e^(z 〖_j〗) = Standard exponential function for output vector
3.4.4 Model compilation
During compilation, three arguments were taken into account.
Loss function - In this classification task, the categorical_crossentropy loss function is applied. This loss is an excellent indicator of how distinct two discrete probability distributions are from one another.
Optimizer - The Adam Optimizer is used to alter the weights and learning rate of neural networks. By minimising the function, optimizers are employed to address optimization issues.
Metrics - Accuracy is used to assess the performance of the Convolutional neural network method.

3.5 Model Training and Model Testing (Blind Testing) with real-time query using enabled web camera
The CNN model is trained on the training dataset using 30 iterations (epochs), with each iteration having 2000 steps. The model.fit() method is used to train our model, which works well following the successful construction of model

architecture. We achieved 99.4 percent accuracy on training sets with 50 batch sizes and achieved stability after 30 epochs with 2000 steps in each epoch.
The value of trainable parameters is adjusted/modified during training according to their gradient. Non-trainable parameters are those whose value is not optimised as a function of their gradient during training. The sum of Trainable and Non-trainable params is Total params.
For blind testing, real-time inputs from our system's embedded web camera were captured using OpenCV and supplied into the system. The model performed admirably even with unknown and noisy inputs.
4. Model Evaluation
Different evaluation measures are utilised to understand the model's performance as well as its strengths and shortcomings, which is an important aspect of model development. It is critical to analyse the model's efficacy early on because it aids with model monitoring.

4.1 Loss Curve
The loss curve depicts the training process and the neural network's learning direction. After each epoch, the graph is plotted. The loss function is calculated across all data items during an epoch and is guaranteed to deliver the quantitative loss measure at that epoch. The learning rate can be estimated by comparing the graph to a reference graph.
The image speaks for itself.It may be estimated that the model has a satisfactory learning rate by comparing the two graphs.

4.2 Accuracy Curve
The accuracy curve is one of the most significant graphs to understand the Neural Network's progress. The curve that includes both training and validation accuracy is more relevant. By comparing the graph to a reference graph, the advancement in the model's accuracy can be evaluated.
Overfitting is seen by the gap between training and validation accuracy. The higher the overfitting, the larger the gap. The model's graph shows a relatively small gap, indicating that it has not been overfitted. The model is providing an accuracy of 99.42% which is pretty good.
6. Limitations
Despite its high level of accuracy, the model has several limits. They are also:
The model fails to capture pose, view, orientation of the images because of the intrinsic inability of max pooling layer.
Image processing should be done properly to detect and focus the sign boards properly and to read the images which are hazy.
7. Conclusion
This project explores the construction of a classification algorithm for the traffic sign recognition problem. When paired with image processing steps, the proposed technique for traffic sign classification produces extraordinarily good results: 99.4 percent of properly classified photographs. The suggested categorization technique is implemented using the TensorFlow framework. The developed method was tested on a device powered by an Intel Core i3 7th Gen Processor. In addition, an audio-enabled system warns drivers and passengers of upcoming traffic signs. In the future, we plan to teach the CNN to consider more traffic sign classes as well as potential severe weather conditions.