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Image Caption Generator using CNN-LSTM Deep Neural Network

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Abstract: ***Captioning pictures naturally is one of the significant aspects of the human visual framework. There are numerous benefits if there is a model which consequently inscription the scenes or climate encompassed by them and offers back the subtitle as a plain book. In this paper, we present a model dependent on CNN-LSTM neural organizations which naturally identifies the items in the pictures and creates inscriptions for the pictures. It utilizes Inception v3 pre-prepared model to play out the errand of distinguishing items and utilizations LSTM to produce the subtitles. It utilizes the method of Transfer Learning on pre-prepared models for the undertaking of item Detection. This model can perform two activities. The first is to recognize objects in the picture utilizing Convolutional Neural Networks and the other is to subtitle the pictures utilizing RNN based LSTM (Long Short Term Memory). It additionally utilizes a bar look for anticipating the inscriptions for example choosing the best words from the accessible corps. In this, we take top k expectations, feed them again in the model and afterward sort them utilizing the probabilities returned by the model. A portion of the product prerequisites of this undertaking is Tensor Flow V2.0, pandas, NumPy, pickle, PIL, OpenCV. A little GUI is made to transfer the picture to the model to create the inscription. The fundamental use instance of this undertaking is to help outwardly debilitated to comprehend the general climate and act as per that. The inscription age is one of the intriguing and centred fields of Artificial Intelligence which has numerous difficulties to survive. Inscription age includes different complex situations beginning from picking the dataset, preparing the model, approving the model, making pre-prepared models to test the pictures, identifying the pictures lastly producing the individual picture-based subtitles.***
Keywords*: *CNN, LSTM, Beam search, PIL, OpenCV.

I. INTRODUCTION

Picture subtitle age has arisen as the most conspicuous and significant exploration field following advances in arrangement demonstrating and picture acknowledgment. The age of inscription from the picture enjoys numerous benefits, beginning from aiding the outwardly debilitated, to empower the programmed and time-productive strategy for marking a huge number of pictures put on the web each day. This region additionally brings condition of-workmanship models in Natural Language Processing and Convolution Neural Networks, the two most unmistakable regions in Artificial Intelligence. We utilize a profound convolutional neural organization pre-prepared model to produce a vectorized execution of a picture that we then, at that point give contribution to a Long-Short-Term Memory (LSTM) organization, which then, at that point creates subtitles. One of the critical angles in the field of Image Captioning is overfitting the preparation information [8]. This is on the grounds that the biggest datasets, like the Microsoft Common Objects in Context (MSCOCO) dataset, just have 160000 named images. Picture inscribing has assorted applications in quite a few fields like biomedicine, web based business, web looking and naval force and numerous others. Online media like Instagram, Facebook can create subtitles every day from pictures The fundamental objective of this paper is to comprehend a tad of information in profound learning systems. We principally utilize two models of Artificial Intelligence Convolution Neural organization and the other is LSTM (Long Short Term Memory).

II. LITERATURE SURVEY

In this part, we audit and comprehend the significant types of existing picture inscribing techniques, and these incorporate recovery-based subtitling, layout-based subtitling, and novel inscription age. Layout-based methodologies have static formats with a few void spaces to produce inscriptions and the subtitle length is fixed and doesn't fluctuate from one picture to another. In these philosophies, various items, ascribes, activities are recognized first, and afterward the vacant spaces left in the formats are involved. For instance, Farhadi et al. utilizes a trio of scene components to fill the format spaces for creating picture inscriptions. Li et al. remove the expressions identified with distinguished items, ascribes, and their connections for this reason. A Conditional Random Field (CRF) is received by Kulkarni et al. to deduce the items, qualities, and semantic jargon before involving the holes. A layout-based methodology can create semantically and linguistically reasonable and exact inscriptions. Notwithstanding, formats are now characterized and can't produce v subtitles of various lengths. Later on, parsing-based designs have been presented in picture inscribing which are more practical and exact than fixed format-based strategies. Thusly, in this paper, we don't focus on these layout-based strategies. Subtitles can be recovered from visual space and multimodal space. In

recovery-based methodologies, subtitles are created from a bunch of the current corpus. Recovery-based strategies initially recognize the outwardly appropriate pictures with their subtitles from the preparation informational collection. These supposed subtitles are called applicant inscriptions. The inscriptions for the question picture are chosen from these subtitles pools. These techniques produce semantically and linguistically precise subtitles. Be that as it may, they can't produce picture-based and completely right inscriptions. Novel inscriptions can be created from both visual space and multimodal space [10]. An overall methodology of this class is to examine the visual substance of the picture first and afterward make subtitles from the visual vectorized content utilizing a language model. These strategies can make new inscriptions for each picture that is semantically more exact than past approaches. Most epic subtitle age models utilize profound AI-based approaches. Subsequently, profound learning-based novel picture subtitle creating techniques are our essential premium in this writing Novel inscription age-based picture inscription models for the most part utilize visual space and profound learning-based models. Inscriptions can likewise be created from multimodal space. Profound learning-based picture inscribing strategies can likewise be arranged on learning procedures: Supervised learning, Reinforcement Learning, and Unsupervised Learning. We sort support learning and unaided learning into other Deep Learning-based procedures. By and large, inscriptions are produced for an entire piece of the picture and not by thinking about some piece of the picture. Be that as it may, subtitles can likewise be made for different pieces of a picture (Dense inscribing). Picture inscribing models can use either basic Encoder-Decoder engineering or Compositional design. A few models utilize consideration ideas, semantic instruments, and various viewpoints in picture portrayal age. A few strategies can likewise make inscriptions for obscured objects in a picture. We bunch them into one classification as "Others". The majority of the picture subtitling strategies use LSTM as a language model. Notwithstanding, various techniques utilize other profound learning designs like CNN and RNN. Hereafter, we consider language model-based classes as LSTM and Others.

III.PROPOSED SYSTEM

The framework we proposed predominantly utilizes two diverse neural organizations to make the inscriptions. The main neural organization is the Convolutional Neural Network(CNN), which is utilized to prepare the pictures just as to identify the articles in the picture with the assistance of different pre-prepared models like VGG, Inception, or YOLO. In this undertaking, we have decided to utilize the initiation v3 model as our convolution neural organization model which is prepared on an imagenet informational index. The second neural organization utilized is Recurrent Neural Network(RNN) based Long Short Term Memory(LSTM), which is utilized to produce subtitles from the created object watchwords. Furthermore, for this venture, we picked the Flickr 30k informational collection where each picture is depicted with 5 inscriptions [9]. As there is a ton of information required to prepare and approve the model, summed-up AI calculations won't work. Profound Learning has been advanced as of late to settle the information imperatives on Machine Learning calculations. GPU-based registering is needed to play out the Deep Learning errands all the more successfully.

Our model for the most part comprises of three phases:

Image Feature Extraction: The highlights of the pictures from the Flickr 30K dataset are gotten utilizing the Inception v3 model and we have picked this for the better exhibition of the model in object distinguishing proof. Since it is exact and better than VGG16. The Inception is a convolutional neural organization that comprises 14 layers, as this model engineering catches on quickly. These are prepared by a Dense layer to deliver a 2048 vector portrayal of the photograph and gave to the LSTM layer.

Sequence Processor: The capacity of an arrangement processor is for dealing with the content contribution by acting like a word-installing layer. The installed layer comprises rules to acquire the fundamental highlights of the content and contains a cover to overlook cushioned qualities. The organization is then associated with an LSTM for the last phase of the interaction of picture inscribing.

Decoder: The last phase of the model consolidates the contribution from the Image extractor stage and the arrangement processor stage utilizing an extra activity then, at that point took care of to a 256 neuron layer and afterward to a last and last yield Dense layer that outcomes in a softmax expectation of the following word in the subtitle over the whole corpus of the jargon which was made and gotten from the content information for example Flickr 30k informational collection that was prepared in the arrangement processor stage.

A. Convolution Neural Network

A Convolutional Neural Network is a Deep Learning model which can take in an info picture, dole out significance (learnable loads and inclinations) to different parts in the picture, and have the option to classify one from the other. The pre-preparing needs in a ConvNet are a lot lower when contrasted with other existing characterization models. While in conventional and crude models channels are hand-designed, with enough preparation, ConvNets have the in-assembled capacity to comprehend and gain

proficiency with these channels. The design of a ConvNet is more like that of the availability example of Neurons in the Human Brain and was inspired by the association organization of the Visual Cortex. Singular neurons react to outside improvements just in a section district of the visual field known as the Receptive Field. A gathering of such assembled fields covers to cover the entire visual base. A ConvNet can effectively catch and comprehend the Spatial and Temporal conditions in a picture through the use of required and significant channels. The model plays out a superior preparation to the picture dataset because of the decrease in the boundaries in question and the reusability of loads. All in all, the organization can be prepared to comprehend the improvement of the picture. The fundamental thought of the Convolution Operation is to acquire the undeniable level highlights of various pieces of a picture like edges, from the given information picture. ConvNets need not be restricted to just a single Convolutional Layer. There can be the arrangement of convolutional layers to a transferred input picture into the layer. Customarily, the principal ConvLayer is answerable for extricating the Low-Level highlights of information pictures like edges, bends, shading, angle direction, and so on with added layers, the engineering adjusts and have the option to get the High-Level highlights also, giving us a model which has the full bundle of comprehension of pictures in the gave dataset, like how an ordinary mind individual attempts to decipher. There are two kinds of results for the applied activity — one in which the convolved highlight is diminished in dimensionality when contrasted with the information, and the other in which the dimensionality is either expanded or stays as before relying on the need and engineering of the picked convolution neural organization model. This is finished by applying Valid Padding on account of the previous, or the Same Padding on account of the last mentioned. Like the Convolutional Layer, the Pooling layer is answerable for diminishing the spatial highlights and size of the Convolved Feature removed from the picture by the convolution layer. This is done to diminish the computational force needed to handle the information through dimensionality decrease and to overfitting the model towards any informational collection gave [3]. Besides, it is more valuable for getting predominant aspects which are rotational and positional invariant, consequently keeping up the interaction of successfully fitting and preparing the design. There are essentially two kinds of Pooling: Max Pooling and Average Pooling. Max Pooling returns the greatest worth from the piece of the picture covered by the channel. It primarily comprises two boundaries channel size and step width. Then again, Average Pooling returns the normal of the multitude of qualities from the piece of the picture covered by the channel. Max Pooling likewise proceeds as a Noise obscuring activity. It eliminates the boisterous initiations out and out and performs de-noising along with dimensionality decrease. Then again, Average Pooling predominantly does dimensionality decrease as a commotion-eliminating system. Thusly, we can say that Max Pooling shows improvement over Average Pooling. The Convolutional Layer and the Pooling Layer, together with the structure the I-th layer of a Convolutional Neural Network. Contingent upon the intricacies in the pictures and kind of utilization this model is applied to, the number of such layers might be expanded for catching minor element subtleties in a picture, however at the expense of more teachable boundaries and computational force. Adding a Fully-Connected layer is a modest method of learning non-straight mixes of the great level highlights as addressed by the yield of the convolutional layer. The Fully-Connected layer is learning a perhaps non-straight capacity in that space. Since we have changed over our info picture into an appropriate structure for our Multi-Level Perceptron, we will straighten the picture into a segment vector. The levelled yield is given to a feed-forward neural organization and backpropagation applied to each cycle of preparing. Over a progression of ages, the model can recognize ruling and certain low-level highlights in pictures and order them utilizing the Softmax Classification method.

B. Transfer Learning

Transfer learning is the most well-known and efficient technique in PC vision since it allows us the opportunity to construct more precise models efficiently and effectively. With this exchange learning, rather than beginning the entire taking in measure from start, we can begin from designs that have been now realized when taking care of an alternate issue by the model. This way we can take the influence of past learnings and abstain from the beginning without any preparation. In PC vision, move learning is generally done using pre-prepared models. A pre-prepared model is a model that was prepared on an enormous benchmark dataset, for example, imagine taking care of an issue like the one that we need to tackle. Likewise, because of the computational expense of preparing such models, for example, requiring enormous datasets and very good quality GPU, it's anything but a typical practice to import and utilize models from effectively being used designs. A thorough survey of pre-prepared models' exhibition on PC vision issues utilizing information from the ImageNet. At the point when we are adjusting a pre-prepared model for our own necessary issue articulation, we start by eliminating the first classifier, then, at that point, we add another classifier that accommodates our difficult assertion, lastly, we need to calibrate our repurposed model as per one of three accessible methodologies: Train the whole model. In this situation, we can utilize the engineering of the pre-prepared model and train it as indicated by the necessities of our dataset. We are making the model to gain without any preparation, so we will require a bigger dataset and a ton of computational force. Train a few layers and leave the others immaculate and frozen. As we realize that, lower layers allude to general highlights (issue autonomous), while higher layers allude to issue explicit highlights. Here, we play with

that polarity by picking the amount we need to change the loads of the organization a frozen layer doesn't change during preparation. For the most part, on the off chance that we have a little dataset and an enormous number of boundaries, we will leave more layers frozen to keep away from overfitting information. Conversely, if the dataset is enormous and the quantity of boundaries is little, we can ad-lib the model via preparing more layers to the new errand since overfitting isn't an issue. Freeze the convolutional base. This case relates to an outrageous instance of the train or freezes compromise. The centre thought is to keep the convolutional base in freeze and afterward utilize its yields to offer it to the classifier. We are utilizing the pre-prepared model as a fixed element extraction component, which can be helpful if we are short on computational force or our dataset is little, or potentially the pre-prepared model takes care of a difficult that is especially like our difficult assertion. In this paper, we are utilizing the third methodology of freezing the convolution base and preparing the classifier part.

C. Recurrent Neural Network

A Recurrent neural network (RNN) is a sort of counterfeit neural organization which utilizes consecutive information or time-arrangement information. These profound learning models are ordinarily utilized for ordinal or transient issues, like language interpretation, normal language handling (NLP), discourse acknowledgment, and picture inscribing; they are joined into mainstream applications like Siri, voice search, and Google Translate. Like feedforward and convolutional neural organizations (CNNs), intermittent neural organizations use preparing information to become familiar with the highlights. They are separated dependent on their "memory" as they take data from earlier contributions to mirror the current info and yield. While old profound neural organizations accept that information sources and yields are free of one another, the yield of intermittent neural organizations relies upon the earlier components inside the arrangement. While future occasions would likewise help decide the yield of a given grouping, unidirectional intermittent neural organizations can't be utilized for these sorts of expectations. Another separating normal for intermittent neural organizations is that they share boundaries across each layer of the organization so it will help in foreseeing the last yield from the gave input consecutive information. While feedforward networks have various loads across every hub, repetitive neural organizations share a similar weight boundary inside each layer of the organization. All things considered, these loads are as yet changed through the cycles of backpropagation and inclination plunge to exploit support learning. Repetitive neural organizations influence the backpropagation through time (BPTT) calculation to decide the slopes, which is marginally not quite the same as old backpropagation as it is explicit to give succession information. The standards of BPTT are equivalent to conventional backpropagation, where the model trains itself by ascertaining mistakes from its yield layer to its information layer. These computations permit us to change and fit the boundaries of the model properly dependent on the acquired blunder. BPTT varies from the customary methodology in that BPTT wholes blunders at each time step while feedforward networks don't have to entirety mistakes as they don't share boundaries across each layer. Through this interaction, RNNs will in general run into two issues, known as detonating slopes and disappearing angles. These issues are characterized by the size of the angle, which is the incline of the misfortune work along the mistake bend. At the point when the slopes are little, it keeps on decreasing, refreshing the weight boundaries until they become valuable for example 0. At the point when that happens, the calculation is done learning and the model doesn't deliver exact yield. Detonating angles happen when the inclination is excessively enormous, prompting a flimsy model. For this situation, the model loads will become excessively enormous, and they will ultimately be addressed as NaN. One answer for these issues is to decrease the quantity of covered-up layers inside the neural organization, disposing of a portion of the intricacy in the RNN model. Feedforward networks map one contribution to one yield and keeping in mind that we've pictured repetitive neural organizations along these lines, they don't really have this requirement [2]. All things being equal, their information sources and yields can shift long, and various sorts of RNNs are utilized for various use cases, like music age, supposition characterization, and machine interpretation. Various kinds of RNNs are accessible like balanced, one-to-many, many-to-one, many-to-numerous for various applications. The drawback of RNN with long haul conditions brings about other model LSTM we will examine in another segment of this paper which is additionally RNN based yet tackles the issue of long haul reliance.

D. Word Embedding's

Word embedding's give a thick portrayal of words as opposed to meagre portrayals of words as of customary models and their relative semantical implications. They are a tremendous improvement over scanty portrayals utilized in a less difficult sack of word model portrayals. Word inserting's can be gained from text information and reused among various ventures. They can likewise be learned as a component of fitting a neural organization on text information. Word installing is a gathering of approaches for addressing words and reports utilizing a thick vector portrayal. It's anything but an improvement over the conventional sack of-word model encoding plans where huge scanty vectors were utilized to address each word or to score each word inside a vector to address a whole jargon. Thus huge vector portrayals require more memory, more teachable boundaries, and bringing about the necessity of high computational force. These portrayals were meagre because the vocabularies were

tremendous and a given word or report would be addressed by an enormous vector involved for the most of zero qualities. All things considered, in an implanting, words are addressed by thick vectors where a vector addresses the projection of the word into a persistent vector space. The situation of a word inside the vector space is gained from the content and depends on the words that encompass the word in the vector space when it is utilized [6]. The situation of a word in the learned vector space is alluded to as its installing. These vectors can be of huge size, for example, 200 or 300 for down-to-earth applications so that covering all semantic implications of the words accessible in the jargon corpus. The two most well-known instances of techniques for taking in word installing's from the content incorporate Word2Vec and GloVe.

E. LSTM

One of the issues of RNNs is the possibility that they could associate past data to the current errand, for example, utilizing past video edges may illuminate the agreement regarding the current casing. On the off chance that RNNs could do this, they would be more valuable. However, can they? It depends. They need to can create present yield over the impact of past long conditions. Now and then, we just need to take a gander at late data to play out the current errand. For instance, consider a language model attempting to foresee the following word dependent on the past ones. On the off chance that we are attempting to anticipate the final say regarding "the mists are in the shading," we needn't bother with any further setting – it's quite clear the following word will be white. In such cases, where the hole between the setting word and the word to be anticipated is little, RNNs can figure out how to utilize the previous data. However, there are likewise situations where we need more settings for example long-haul conditions. Considering to anticipate the final say regarding the content "I experienced childhood in Spain… I talk familiar Spanish" Recent data recommends that the following word will be the name of a language, however, if we need to limit to which language, we need to have the setting of the nation for example for this situation it is Spain, from further back. It's completely workable for the hole between the setting data and where it is should have been anticipated to turn out to be extremely enormous. In this way, as the hole turns out to be huge, RNNs tend to not figure out how to associate the data needed to foresee the necessary word. In principle, RNNs are unquestionably fit for taking care of such "long-haul conditions." A human could pick boundaries for them to tackle straightforward issues in this situation. In any case, in genuine cases, RNNs are not skilled to have the option to learn them all alone without outside taking care of them. The issue was investigated top to bottom by, who tracked down some beautiful central reasons why it very well may be troublesome. This prompted the inspiration of looking for another reasonable model of taking care of long-haul conditions. Fortunately, LSTMs are advanced or planned. Long Short Term Memory organizations – normally called "LSTMs" – are an uncommon sort of RNN, fit for learning long haul conditions all alone. They were presented by Hochreiter and Schmidhuber (1997) and were re-imagined and promoted by numerous individuals in the accompanying work. They function admirably on an enormous assortment of issues, and are currently generally utilized, and can deal with each such case in viable applications. LSTMs are unequivocally intended to keep away from the drawn-out reliance issue that is experienced in RNN. Recollecting data for significant stretches of time is for all intents and purposes their default conduct, not something they disapprove of dealing with.

All repetitive neural organizations have the type of a chain of rehashing conditions of neural organizations. In standard RNNs, this rehashing module will have an extremely straightforward design, for example, a solitary tanh layer. LSTMs additionally have this chain-like construction, yet the rehashing module has an alternate design contrasted with RNN. Rather than having a solitary neural organization layer, there are four, communicating in an extraordinarily planned way. The LSTM can eliminate or add data to the phone state, painstakingly controlled by structures called entryways. So with this model can recall what is needed from past data and store them and dispose of any remaining immaterial information.

Doors are an approach to let data to consider or dispose of. They are made out of a sigmoid neural net layer and a pointwise duplication activity. The initial phase in our LSTM is to choose what data we will dispose of from the cell state. This choice is made by a sigmoid layer called the "neglect entryway layer." The following stage is to choose what new data we will store in the phone state. This has two sections. Initially, a sigmoid layer called the "input entryway layer" chooses which esteems we will change. Then, a tanh layer makes a vector of new qualities, that could be added to the state. In the subsequent stage, we'll join these two to make an update to the state. It's presently to refresh the old cell state, into the new cell state from the consolidated data. The past advances previously chose what to do, we simply need to really do it. At long last, we need to choose what we will yield. This yield will be founded on our cell state however will be a separated variant. In the first place, we run a sigmoid layer which chooses which parts of the cell state we will yield. Then, at that point, we put the cell state through tanh and increase it by the yield of the sigmoid entryway, so we just yield the parts we chose to and produce the required sequential output.

F. Model Summary

We will describe the model in three parts:

1) *Feature Extractor:* The element separated from the picture has a size of 2048, with a thick layer, we will decrease the measurements to 256 hubs.

2) *Sequence Processor:* An inserting layer will deal with the text-based info, trailed by the LSTM layer.
3) *Decoder:* By blending the yield from the over two layers, we will measure by the thick layer to make the last forecast. The last layer will contain the number of hubs equivalent to our jargon size.

This is to decrease the overfitting of the preparation dataset, as this model arrangement catches on quickly. The Decoder model unions the vectors from both information models utilizing an expansion activity. This is then taken care of to a Dense 256 neuron layer and afterward to a last yield Dense layer that makes a softmax forecast over the whole yield jargon for the following word in the grouping [5]. This is the plot made to comprehend the design of the last entire model that better comprehends the two sorts of info one coming from the origin v3 model and the other coming from LSTM which are consolidated and given to the full associated layer for the learning cycle. The entire model can be seen underneath in figure 1.

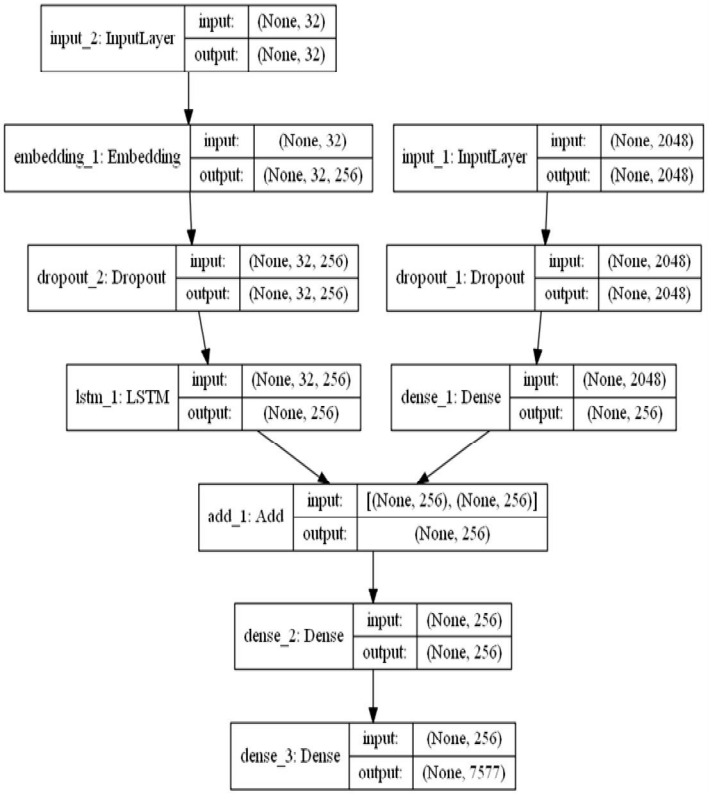

Figure 1. Model Summary.

Figure 1 shows the block diagram of the proposed model and summary of the model with vector sixes of both input and output size after coming out of that layer.

IV. RESULTS

So our paper mainly used two models inception v3 for generating feature map of given image and LSTM model which is a kind of RNN for sequence modelling of captions. These two outputs are merged and are trained on fully connected layer or feed forward neural network on Flickr 30k data set. The model is then compiled and saved to avoid re-training. The model weights for inception v3 are downloaded to avoid re-training of model. The model training took much time since large data set is used. After training the model is tested with images from Flickr 30k dataset and model generated accurate captions for the respective images. A small GUI is created for uploading the image into model and generating the captions. In this way by using multi-modal network i.e. blending of convolution neural network with recurrent neural network the captions of input image are being able to be generated by the reading the whole image and performing object detection and by using sequence modelling of recurrent neural network required captions for the image input are being generated. The result of the project is generated when we upload an image from the local computer. After uploading when we click on generate button it's the model will be called and captions are generated for the respective image. The model is able to generate three captions for a given image and best caption can be selected by seeing which is more suitable for the provided image.

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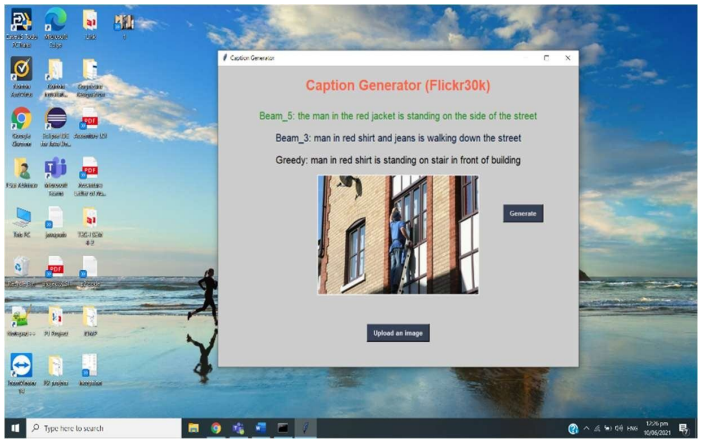

Fig 2: Captions generated for uploaded image

Figure 2 shows the GUI created for the model to upload the image and after clicking the button generate captions we can the see the generated captions by the model for the image.

V. CONCLUSION

In this paper, we introduced a multi-model Neural Network that consequently figures out how to depict the portrayal of pictures. Our model initially acquires the data of articles present in the picture and their spatial areas in a picture, and afterward, a profound intermittent neural organization (RNN) in light of LSTM units produces a depiction sentence appropriate to the picture. Each expression of the depiction is consequently intended for various items that show up in the information picture when it is created. The proposed model is more advanced contrasted with other benchmark calculations on the ground that its execution is completely made on the human visual framework. The CNN-LSTM model was based on making the inscriptions for the information pictures. This model can be utilized for an assortment of uses, for example, assisting the outwardly disabled individuals with understanding the climate wherein they are in by utilizing text to discourse transformation instrument and naming the pictures that are put on inward efficiently and effectively. In this, we examined the CNN model, RNN models, LSTM models, and eventually, we approved that the model is making subtitles for the information pictures. Picture inscribing has made critical advances as of late and developed a great deal and it's anything but a more successful state. Late work dependent on profound learning procedures has brought about a forward leap in the precision of picture subtitling. The content depiction of the picture can definitely improve the substance-based picture recovery proficiency, the growing application extent of visual comprehension in the fields of medication, security, military, and different fields, which has a wide application prospect. This philosophy of consolidating two unique models of profound learning can be extremely valuable and can be applied in numerous different applications. This multi-model neural organization approach would be exceptionally useful later on and can be applied in countless applications.

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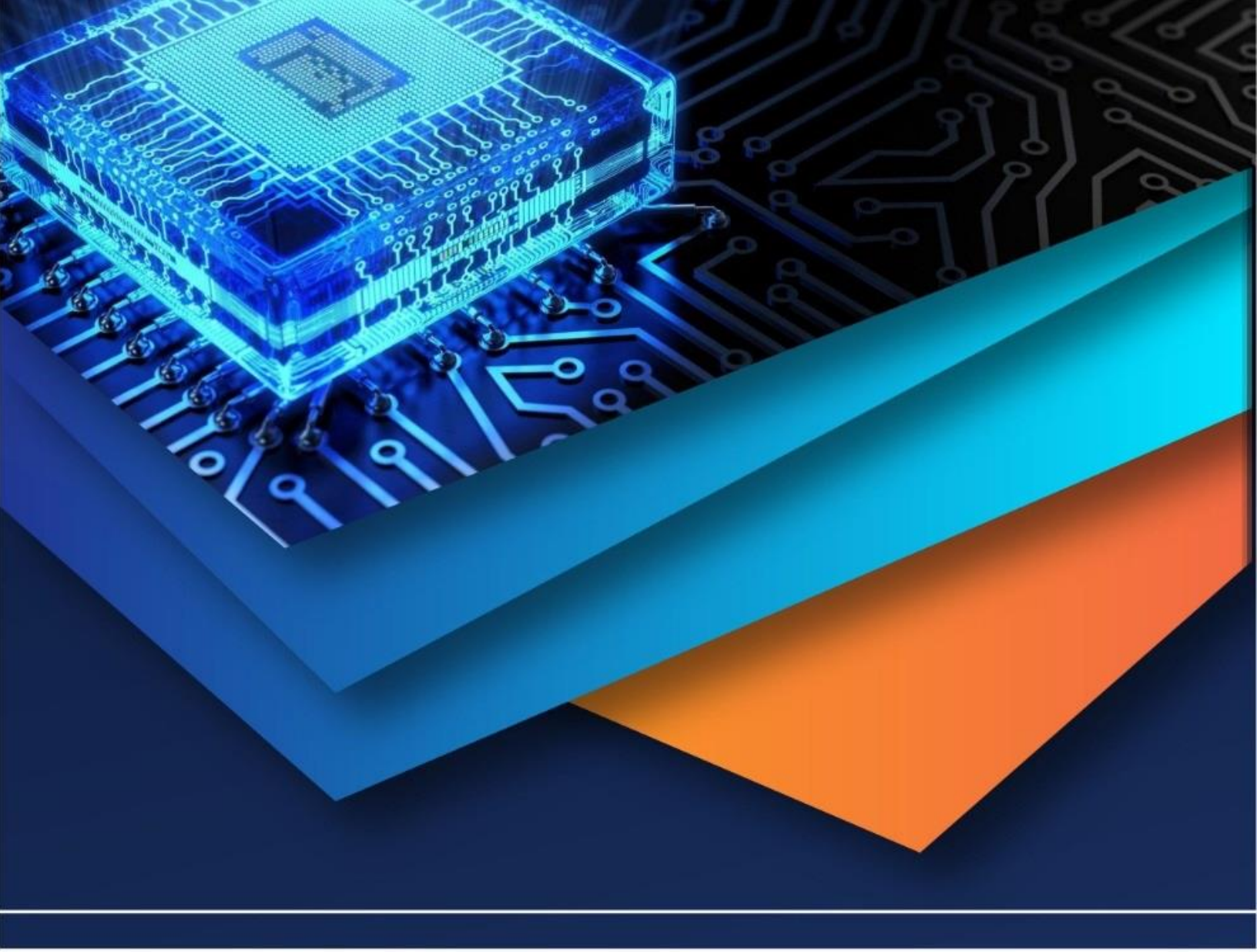

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