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Detection of Brain Hemorrhage

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Abstract: One of the top 5 disorders that cause death is intracranial hemorrhage. To relieve busy radiologists and identify patients in need of rapid treatment, we attempt to automate the process of identifying these bleeding in this research. we experimented with three different pretrained models, namely ResNet101, DenseNet121, and AlexNet, to improve the accuracy of their classification model. We observed that switching from ResNet50 to ResNet101 led to a modest increase in accuracy from 91.3% to 91.7%. However, using DenseNet121, which has a unique architecture where each layer receives collective knowledge from all previous layers, resulted in the highest accuracy of 91.8%. On the other hand, AlexNet, a well-known architecture that won the 2012 ImageNet competition, had a shorter training period but achieved a lower accuracy of only 89%.

I. INTRODUCTION

One of the top five global causes of mortality is intracranial hemorrhage, sometimes known as brain hemorrhage. The illness is brought on by bleeding inside the cranium, commonly known as the skull. It is critical to get a prompt and correct diagnosis because this form of hemorrhage accounts for about 10% of strokes in the United States. Effective management of the illness and avoidance of its serious effects depend on an accurate diagnosis, underscoring its crucial importance in patient care.

The magnitude, kind, and location of an intracranial hemorrhage, often known as brain bleeding, can have a variety of effects. These variables interact intricately, and a tiny hemorrhage in a crucial area may be just as lethal as a bigger one. Rapid diagnosis is essential in these situations, especially for those displaying severe hemorrhage signs like unconsciousness. The diagnostic and treatment procedure, however, is frequently challenging and time-consuming, resulting in considerable delays and unfavorable patient outcomes, particularly for those who require urgent care. This study attempts to overcome this difficulty by automating the first classification of the bleed's size, location, and kind using an algorithm. With the algorithm treating every scan similarly to reduce human error and increase accuracy, clinicians are able to diagnose patients more quickly and accurately.

In order to improve the diagnosis process and eventually result in improved patient outcomes, this research intends to create an algorithm capable of properly recognizing acute cerebral hemorrhage and its subtypes. A major step towards overcoming the difficulties involved in diagnosing and treating cerebral hemorrhage will be reached with the effective identification of these essential characteristics. The algorithm will shorten the diagnostic process and lower the chance of mistakes by automating this process, allowing medical practitioners to diagnose patients more quickly and accurately.

II. BACKGROUND AND RELATED WORK

Deep learning has been used more and more in medical imaging during the past ten years, making it possible to identify pneumonia using chest X-rays or retinal to diagnose diabetes. Image segmentation has been used to automate measurements of organs, cell counts, and simulations. It has also been used to color-code images and extract boundary information. In a recent study, the Qure.ai team used convolutional neural networks (CNNs) and natural language processing (NLP) methods on related medical records to identify MRIs using deep learning. The research, which had trouble with 3D scans, examined 313,318 anonymous CT scans from several centers across India. The dataset had a mean age of 43.4 years, and 42.87% of the people were female. The study's overall AUC for all sub-categories was 0.94 ± 0.3. Other important studies include acute cerebral hemorrhage on head computed tomography expert-level identification, extracting 2D weak labels from volume labels using multiple instance learning, and extracting 2D weak labels from volume labels. In a subsequent study, they aggregated the losses per slice derived from bags of 2D slices to update the model's parameters.

III. IMPLEMENTATION

A. Data Cleaning

Both picture data and metadata are included in the 194082 DICOM pictures in the collection, with the metadata lacking any private information to protect data privacy. Because using the DICOM format may result in lengthy processing times, the metadata is converted into a data frame. This allows for speedier and more efficient processing. We next show the cross-sectional brain scans so that the dataset may be understood better. Filtering out blank slices is done using the "img pct window" column, which displays the percentage of brain pixels in each slice. Pictures having a value in this column of less than 20% are removed.

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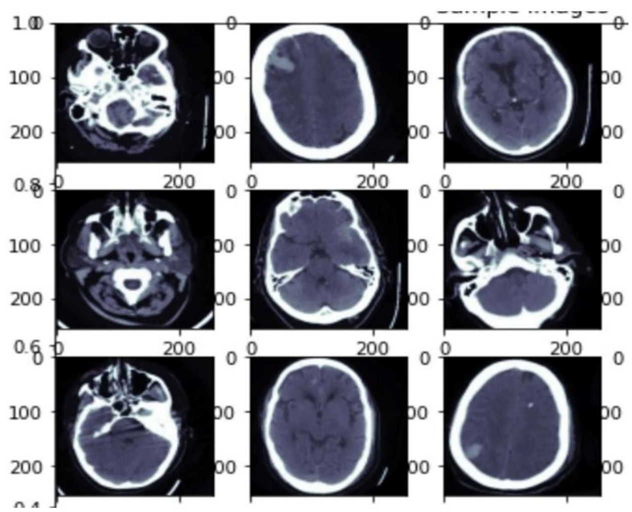
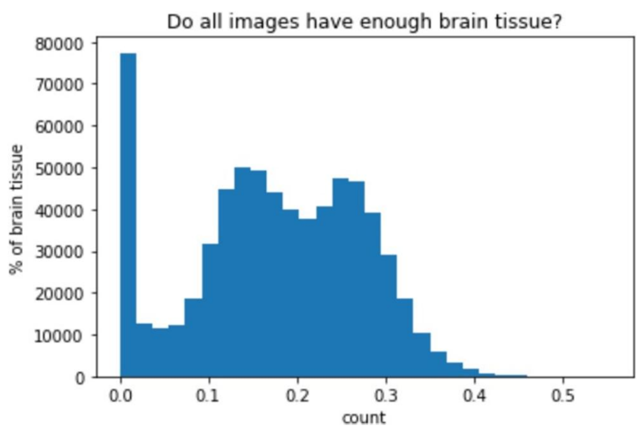
Sample Images

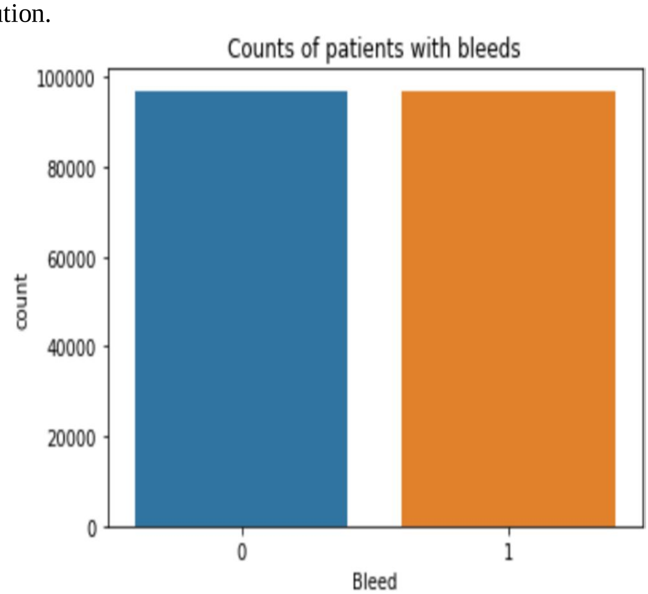




Additionally, we adjust the Rescale_Intercept column, resize and crop the photos to (256,256), and then we save them as ".jpg" files.

B. Data Exploration

We examine the data's distribution.



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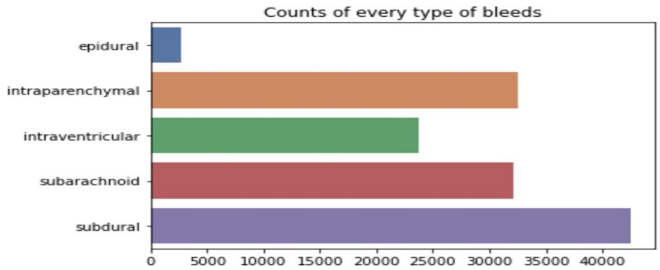
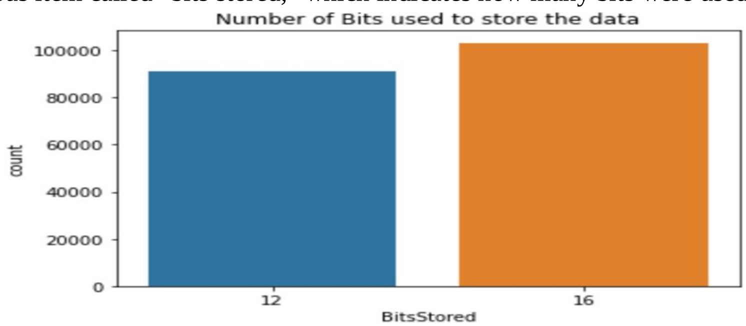
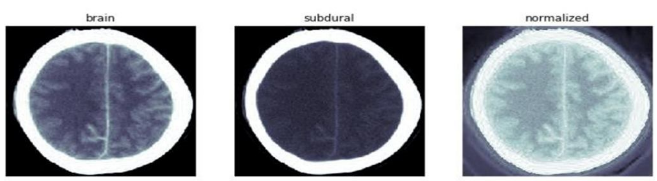
Our dataset shows a reasonably balanced proportion of photos showing both cerebral haemorrhages and non-hemorrhagic instances, according to a rigorous study. The prevalence of each form of haemorrhage in the dataset has also been carefully investigated.



According to our observations, the "subdural" form of haemorrhage occurs most frequently in our sample. We next looked at the informatizn and found a curious item called "bits stored," which indicates how many bits were used to store the data.



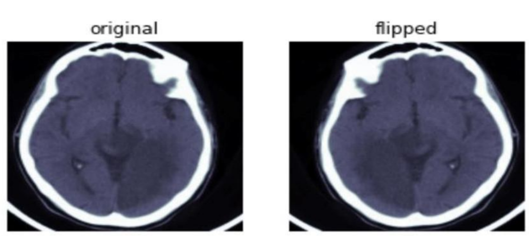
Given the disparity in the "bits stored" column, it's possible that the dataset came from two different companies. We will use this data for our study even though deep learning models often perform better when the data comes from the same distribution.
Finally, other windows may be used to see the images.



But it's important to recognize that windowing is a method for improving how medical pictures are seen by people. Deep neural networks, on the other hand, function with floating point data and don't need windowing for processing.

C. Data Augmentation

The availability of a sizable dataset is essential for training an effective deep learning model. This might not always be possible, though. As a result, we may modify the pixel values rather than the contents of the image as perceived by humans by applying modest, random adjustments to the current data. The model's capacity to generalize may be strengthened, and performance can be enhanced, by including data augmentation techniques into the training process.
The transformations that may be applied to our data are listed below.
Flip: The model is exposed to more instances of bleeding occurring on multiple sides of the brain by the act of flipping the pictures, which improves its capacity to think through potential scenarios.



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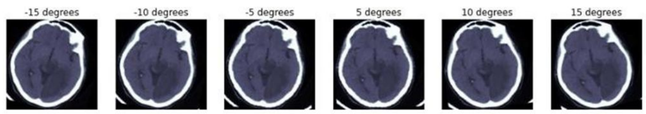
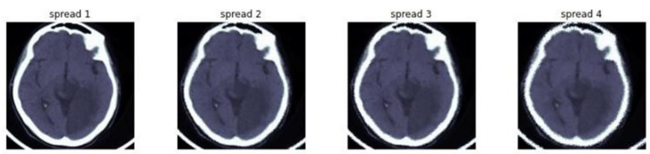
1) *Rotation:* To take into consideration the variance in slice orientation, we randomly rotate a few pictures between We randomly rotate a few photos within the range of (-15, 15) degrees throughout the data augmentation procedure to account for the diversity in the orientation of slices.



2) *Blur:* We add a blurring effect to a few selected pictures to account for the likelihood that a patient's movement during an MRI might lead to blurred images. From left to right, the blur's intensity gradually increases in a sequential way.

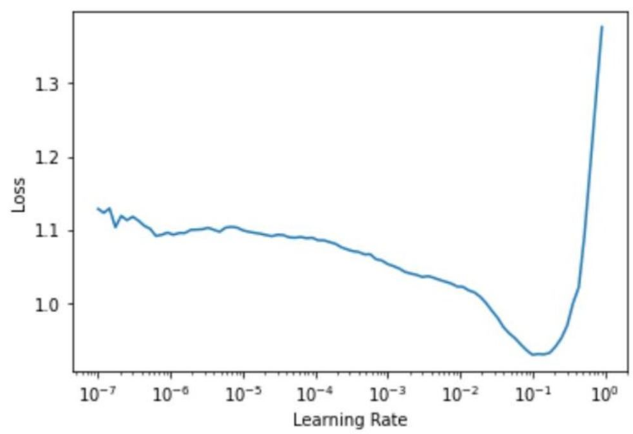
D. Modelling



1) Binary Classification

Recent research has shown that metadata can help in picture categorization. Our first plan was to use both photos and information to do the categorization assignment. We sought to categorize hemorrhages using just information to assess their efficacy. But even with a strong model like Random Forest, we found that the accuracy was just 50%. Therefore, we decided to ignore the information and focus just on the photos.

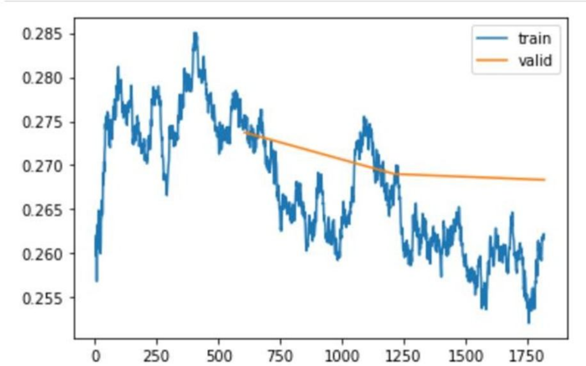
ResNet18 was the model we used for our baseline model. Transfer learning has shown promising results in picture categorization while also significantly cutting down on training time and resource use. We utilise Leslie Smith's learning rate finder to choose an appropriate learning rate.[5]



This approach involves doing a training loop on the data while changing the learning rate from a very low value to a high value of 10. The best learning rate that minimizes loss is then identified and compared to the other learning rates. With the batch size set to 256, 20% of the data are randomly chosen as the validation set. We change hyperparameters using Leslie Smith's one cycle training method [4]. We freeze the pretrained section of the model and train just the new head in order to maintain a mean of 0 and a standard deviation of 1 for each layer. Our model was accurate to about 89% of the true value.

epoch	train_loss	valid_loss	error_rate	accuracy	time
0	0.268112	0.266647	0.111629	0.888371	11:24
1	0.264794	0.265100	0.110753	0.889247	11:26
2	0.262578	0.265090	0.110959	0.889041	11:20

Plot of the loss is as shown below:

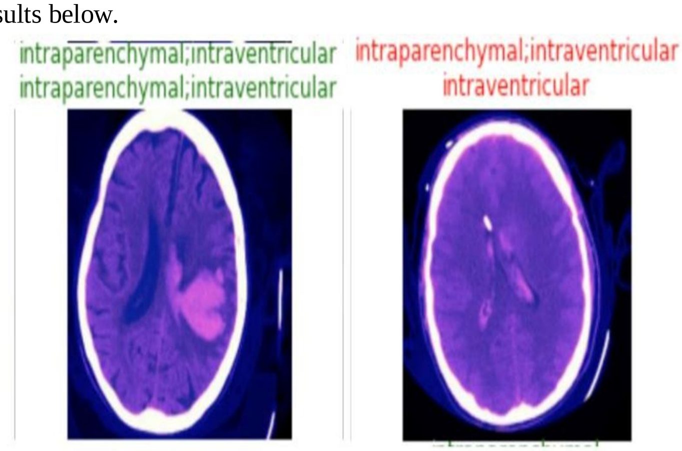


2) Multilabel Classification

We implement the restriction of only including bleed-containing pictures in Multilabel Classification. Additionally, we add a new column to our data frame that lists each of the semicolons-separated subcategories of bleeds that are present in each picture. ResNet50 is the pretrained model we use for this job, and all other hyperparameters—aside from the accuracy metric—remain the same as those we used for binary classification. Setting a threshold number, which in our application is 0.5, is the first step in our methodology. We choose all the classes whose values are higher than our threshold value rather than the maximum value from our sigmoid outputs. By doing this, we may produce many classes for each image, which we can compare to the real-world data to see how accurate they are. This is how our new accuracy formula is presented:

```
def accuracy_multi(inp, targ, thresh=0.5, sigmoid=True):
    "Compute accuracy when `inp` and `targ` are the same size."
    if sigmoid: inp = inp.sigmoid()
    return ((inp>thresh)==targ.bool()).float().mean()
```

Approximately 91.3% of the time, the present architecture has worked well. The pretrained ResNet model is made up of a number of res blocks, sometimes called skip or identity connections. Because it overcomes the issue of gradient diffusion, the ResNet has been a breakthrough in picture categorization. The ResBlock architecture looks like this and is frequently used: By integrating skip connections, often referred to as identity connections, between convolutions, the ResBlock design addresses the gradient diffusion issue. Every two convolutions in this design, the input is added to the output. The output is changed from: if we think of the convolutions as functions, to: Some of the outcomes that we got are listed below. Each image in the output is accompanied by two lines, where the upper line represents the predicted value, and the lower line represents the actual value. The text in green color denotes a correct prediction, while the text in red color denotes an incorrect prediction.
We can view some of the results below.



The top line of each output graphic represents the forecast, while the bottom line displays the actual value. Red denotes a prediction that was made wrong, while green denotes a prediction that was right.

IV. MODEL OPTIMIZATION

A. Different Architectures

1) ResNet101

The simplest technique to improve a classification model's accuracy is to add more layers, which may be done in any situation. As a result, we switch ResNet50's pretrained model to ResNet101's. As a result, our accuracy rises from 91.3% to 91.7%.

2) DenseNet121

We tested a novel architecture called DenseNet121, whose distinguishing feature is that each layer receives collective knowledge from all earlier levels. The result of a convolution in this architecture is combined with the input before being transferred to the following layer. However, a smaller batch size is necessary due to the increasing number of parameters. We managed to get a 91.8% accuracy using DenseNet121.

3) AlexNet

We tested the well-known AlexNet design, which won the 2012 ImageNet competition. In this design, which also learns quickly, overlap pooling is used to reduce the network size. Despite having a shorter training period, the design did not perform as well as the other ones we tried. We only achieved 89% accuracy on AlexNet.We tested the well-known AlexNet design, which won the 2012 ImageNet competition. In this design, which also learns quickly, overlap pooling is used to reduce the network size. Despite having a shorter training period, the design did not perform as well as the other ones we tried. We only achieved 89% accuracy on AlexNet.

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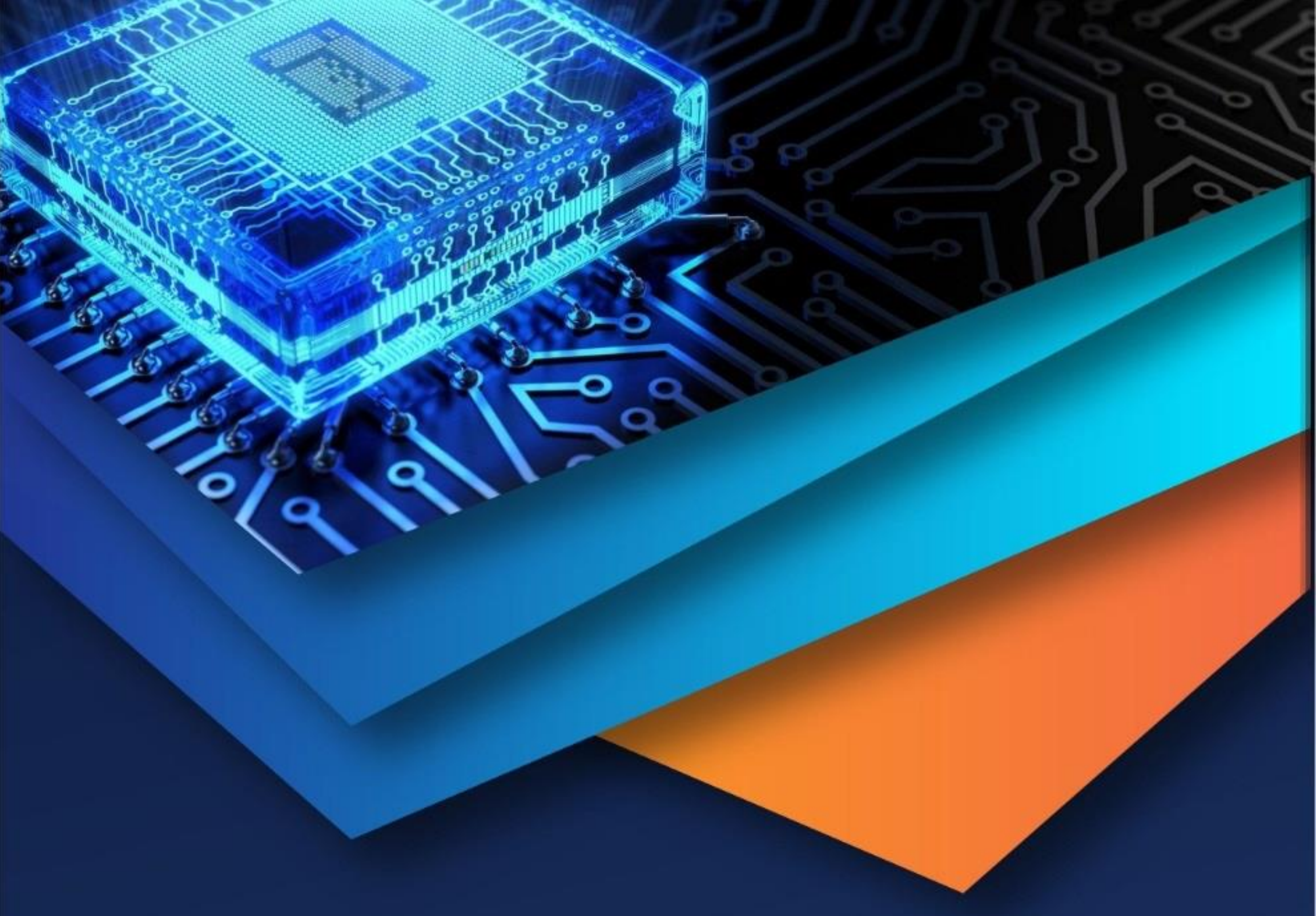

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