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Pneumonia Detection on Chest X- Ray using Deep Learning

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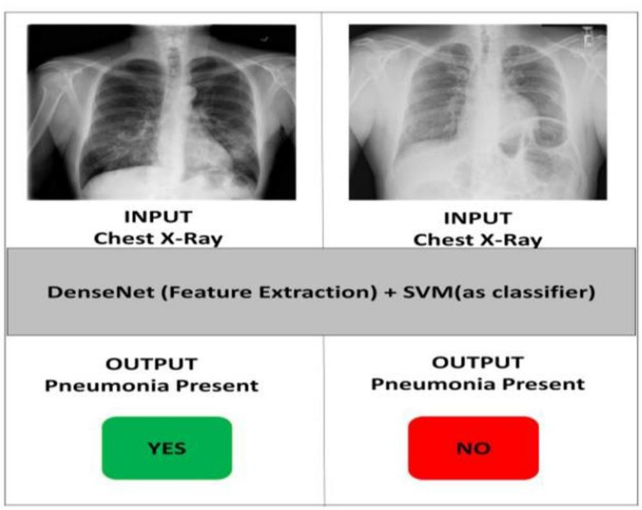
Abstract: In recent years, Pneumonia has become a serious issue in people. The pneumonia which affects the lungs in a way by accumulating the fluid in the lungs. This pneumonia should be treated effectively and should be identified in early stages. The inaccuracies of some algorithms had created problems in diagnosing pneumonia. We came up with an idea to detect pneumonia by taking Chest X-rays and applying a novel algorithm which includes Feature maps, gradient vanishing, skip connection and faster training of the model, minimum computation. This could bring significant impact and help the doctors to identify the pneumonia on their knowledge as we will train the model with different images and we identify Pneumonia effectively.
Keywords: Chest X-rays, Feature maps, gradient vanishing, skip connection

I. INTRODUCTION

The population is increasing day by day, time has become the main priority for the people and detection of the diseases should be done at the earliest to ensure the right treatment for the people.

The WHO has recorded a significant increase in the pneumonia cases which can become a problem and some cases which are even difficult for the doctors to identify the pneumonia. The diet and lifestyle of this generation which is not so good and healthy causing the immunity breakdown and allow diseases to affect the people more often. Pneumonia which affects the breathing of an individual which can be a major issue and treating pneumonia at less time should be done.

Identification of pneumonia is done in an accurate manner using deep learning techniques by classifying images. This gives best results even in the remote areas where the doctors and some equipment are not even available. The people can get best use of these deep learning techniques in identifying pneumonia on chest X-ray. The figure 1 shows the chest X-ray of pneumonia and without pneumonia cases.



The motivation to take on a pneumonia detection using chest x ray project using DenseNet and ResNet is to increase the accuracy and speed of diagnosis. By utilizing these two powerful deep learning architectures, a computer model can be trained to recognize patterns in x-ray images that can be used to detect the presence of pneumonia. By having access to a more accurate and faster diagnosis, healthcare providers can make better decisions about patient care and treatment, leading to better outcomes for patients. Additionally, this method may reduce the amount of time and resources required for diagnosis, leading to cost savings for healthcare providers.

II. PROBLEM STATEMENT

Pneumonia is a serious respiratory infection that affects a significant number of individuals worldwide. Early and accurate detection of pneumonia is crucial for timely treatment and improved patient outcomes. However, manual interpretation of chest X- ray images for pneumonia diagnosis is time- consuming and subject to human error. Therefore, there is a need for an automated system that can effectively classify chest X-ray images and accurately detect pneumonia.

Existing approaches for pneumonia detection often rely on single pre-trained models, limiting their ability to capture diverse and complex image features. Moreover, these approaches may suffer from overfitting and suboptimal generalization due to limited training data.

The goal of this research is to develop a robust and accurate pneumonia detection model by leveraging the strengths of multiple pre-trained architectures.

By combining the feature representations learned from DenseNet121 and ResNet50 models, we aim to enhance the model's ability to extract relevant features and improve its performance in pneumonia classification.

The proposed model will be trained using a combination of data augmentation techniques and a combined generator approach. This training methodology aims to enhance the model's generalization capability, mitigate overfitting, and improve its performance on unseen chest X-ray images.

By addressing these challenges and developing an accurate pneumonia detection model, this research aims to contribute to the advancement of automated medical image analysis systems and improve the efficiency and accuracy of pneumonia diagnosis.

III. LITERATURE SURVEY

A. Existing Systems

In this paper [1], Convolutional Neural Network (CNN) models are proposed for accurately detecting pneumonic lungs from chest X-rays, which can be practically implemented in medical practice for the treatment of pneumonia. The proposed pneumonia detection system is based on the Densely Connected Convolutional Neural Network' (DenseNet-169). The solution to the problem was achieved using a 121- layer Dense Convolutional Network (DenseNet) that had been trained on the Chest X-ray 14 dataset. The weights of the network were initialized with those of a model pretrained on ImageNet, and the network was trained in an end-to-end fashion using Adam with a minibatch size of 16 and standard parameters. The initial learning rate was set at 0.001, and it was decreased by a factor of 10 whenever the validation loss plateaued. According to [3], a single model was implemented using an SSD RetinaNet with SE- ResNext101 encoder pre-trained on ImageNet and ensembled over four folds and several checkpoints to address the problem. The model employed [4]a convolutional architecture in which a dropout layer was integrated with a convolutional layer, followed by a pooling layer. This pattern was repeated multiple times, each convolutional block containing a batch normalization layer and rectified linear unit (ReLU) activation function. Subsequently, the outputs from the convolutional layers were flattened and linked to fully-connected dense layers for classification. The SoftMax activation function was employed at the end of this process to predict probabilities in the last layer.[5] utilized a supervised learning methodology involving Convolutional Neural Networks (CNNs) to address the problem. The CNNs were trained on a dataset of chest X-ray images and their corresponding labels. The input images were classified as either Pneumonia or Normal using the trained CNNs. Backpropagation and stochastic gradient descent were both employed during the training process of the model. Finally, accuracy, precision, recall, and F1 were all utilized to evaluate the model's performance. The methodology employed in [6] for deep learning with convolutional neural networks involves the detection of features automatically, the utilization of activation functions for decision-making in data manipulation, the implementation of padding and pooling layers for dimensionality reduction, dropout layers to reduce overfitting, and fully connected layers to transform multi-dimensional data into single- dimensional data.

In the research [7], a convolutional neural network (CNN) was utilized to classify chest Xray images into two categories: pneumonia or normal. The dataset employed for this research was obtained from Guangzhou Women and Children's Medical Center,Guangzhou, and is publicly accessible on Kaggle. This dataset contains 5856 chest X-ray images (JPEG). The dataset is divided into three folders, labelled as train, val, and test, which are used for training, validation and testing purposes respectively. The methodology used [8] for pneumonia identification in chest X-ray images is an approach based on deep learning. Specifically, a convolutional neural network (CNN) was employed, utilizing a multi-stage training process. Preprocessing of images and data cleaning were initially conducted to reduce noise. Subsequently, data augmentation techniques were applied to increase the diversity of the dataset. The CNN model was then used to train the data before evaluating model performance. The paper[9] employed a model to address the class imbalancement problem consisting of two phases, pre- processing and model architecture.

The pre-processing phase involved converting X-Ray images to the desired size/aspect ratio and employing data augmentation techniques, including Vertical and Horizontal Shift Augmentation, Vertical and Horizontal Flip Augmentation, Random Rotation Augmentation, Random Brightness Augmentation, and more to artificially increase the dataset size. The CRISP-DM [10] methodology was employed for this Data Analytics development project, which is composed of six steps: Business Understanding, Data Understanding, Preparation of Existing Data, Modeling, Evaluation and Implementation.

This paper[11] assesses the performance of LeNet5, AlexNet, MobileNet, ResNet18 and Vision Transformer models for pneumonia recognition. The most suitable models for various scenarios were identified and applied for pneumonia recognition in order to improve accuracy and protect people's health. Initially, chest X-ray images of pneumonia patients and normal subjects were collected and organized with the intention of creating an appropriate dataset for deep learning. The proposed model [12] incorporates a DW-CNN with data augmentation and CNN to detect pneumonia. The algorithm comprises 10 layers of CNNs and the model was trained on pre-trained weights of VGG16 utilizing transfer learning. This model entails a feature extractor or feature detector, as well as a classifier (sigmoid function). The Relu activation function is employed between each layer, while the dropout is set to 0.7 for the first dense.

This paper employed a Convolutional Neural Network (CNN) as its methodology. This convolution is composed of several layers of convolutional filters, which are augmented with activation functions and optimizers in order to improve performance. The workflow began by importing the dataset from Kaggle and then proceeded to process it. Subsequently, the dataset was trained with the VGG16, VGG19, andResNet50 models. The proposed methodology in [14] utilizes transfer learning and evaluates the performance of leading pre-trained convolutional neural networks (CNNs) to solve the image-based pneumonia classification issue. Moreover, data augmentation is implemented to enhance the generalizability of the deep learning model and tackle the overfitting issue. The CNN architecture based on DenseNet-161 is presented in Figure 3. Training a deep network with millions of parameters from scratch would require weeks; thus, transfer learning is employed to leverage existing pre-trained networks. This study [15] employed a hybrid approach combining deep learning and conventional classification methods. Specifically, deep learning models were utilized to extract features from chest X- ray images, which were then incorporated as input for traditional classifiers such as support vector machines (SVM), k-nearest neighbors (KNN), stacked auto- encoders (SAE), and artificial neural networks (ANN) to diagnose pneumonia.

B. Summary

The present systems for detecting pneumonia disease using chest X-ray images through deep learning include DenseNet, Resnet, Xception, VGG but they miss out some features while detecting pneumonia. In the case of detection and classification of pneumonia which differs from algorithm to algorithm even with the small variation in the images of chest X-rays. Hence a approach has been proposed by taking the feature maps, skip connections from the Densenet and Resnet algorithms to make training faster for the model and achieve a better miss out traits in the chest X-ray images. After the training and classification is done, it is passed for testing the model accuracy and is verified whether the target is achieved by the novel algorithm or not. finally, deploying the model in the real world.

IV. METHODOLOGY

A. Preprocessing:

Chest X-ray pictures utilized in this study to identify pneumonia make up the dataset. The photos were subjected to a number of preprocessing procedures before model training. The training, validation, and test photos were separated into the three directories named train, val, and test, which were used to organize the dataset.Data augmentation approaches were used during training to improve the model's performance and increase its capacity for generalization. Using the ImageDataGenerator module from the TensorFlow library, the training data was supplemented. The use of numerous augmentation procedures, such as rotation, shifting, shearing, zooming, and horizontal flipping, was made possible by this module. These modifications added variances to the training images, giving the model a more varied sample set and facilitating more accurate feature extraction.

The photos were subjected to certain preprocessing algorithms to ensure compatibility with the selected model architectures. Different preprocessing procedures are needed for the ResNet50 model and the DenseNet121 model. The required preprocessing functions, densenet_preprocess_input and resnet_preprocess_input, were configured to be used by the ImageDataGenerator objects. By aligning the pixel values of the photos with the preprocessing used during the pretraining of the corresponding models on the ImageNet dataset, these functions standardized the pixel values of the images.

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The preprocessing stage's overall goal was to get the chest X-ray pictures ready for the ensuing model training. The development of a substantial and representative training dataset resulted from the combination of data augmentation approaches and model-specific preprocessing, ultimately enhancing the model's capacity to learn discriminative features and carry out precise pneumonia diagnosis.

B. Model Architecture:

The strength of two pre-trained models, DenseNet121 and ResNet50, is combined in the suggested model architecture for pneumonia identification from chest X-ray pictures. Both models reveal deep hierarchical features that are essential for precise image categorization and have demonstrated great performance across a range of computer vision tasks.

Pre-trained weights from the ImageNet dataset were imported into the DenseNet121 model, giving chest X-ray pictures a powerful beginning representation. On top of the DenseNet121 model, a GlobalAveragePooling2D layer was built to minimize spatial dimensions and capture the most useful features. By randomly turning off a portion of the neurons during training, dropout regularization was used to reduce overfitting. This regularization methodpromotes the model to learn representations that are more reliable and generalizable.

Likewise, pre-trained ImageNet weights were used to initialize the ResNet50 model. High-level features were extracted from the output feature maps of the ResNet50 model using the GlobalAveragePooling2D layer. In order to improve the model's generalization capabilities and avoid overfitting, dropout regularization was used.

The outputs of DenseNet121 and ResNet50 were concatenated using the Concatenate layer to combine their feature representations. The goal of this feature integration was to take advantage of the distinctive advantages of each model and produce a more thorough representation of the input chest X-ray pictures. The model could capture both local and global information by integrating the feature maps, creating a richer and more discriminative representation.

A fully connected layer with a sigmoid activation function was then given the concatenated characteristics, producing a binary classification output indicating the presence or absence of pneumonia. This last layer provided a likelihood score for pneumonia diagnosis and acted as the model's decision-making element.

The Adam optimizer was used to create the merged model, and a learning rate of 0.001 was used. The difference between true and predicted labels was calculated using the binary cross-entropy loss function. Additionally, accuracy was used as an evaluation metric to gauge how well the model performed in classifying data.

The suggested model architecture sought to enhance the accuracy and robustness of pneumonia identification from chest X-ray pictures by utilising the characteristics of DenseNet121 and ResNet50 and merging their feature representations. The combination of information from the two models gave the model a more thorough grasp of the input photos, allowing it to produce predictions that were more well- informed and precise.

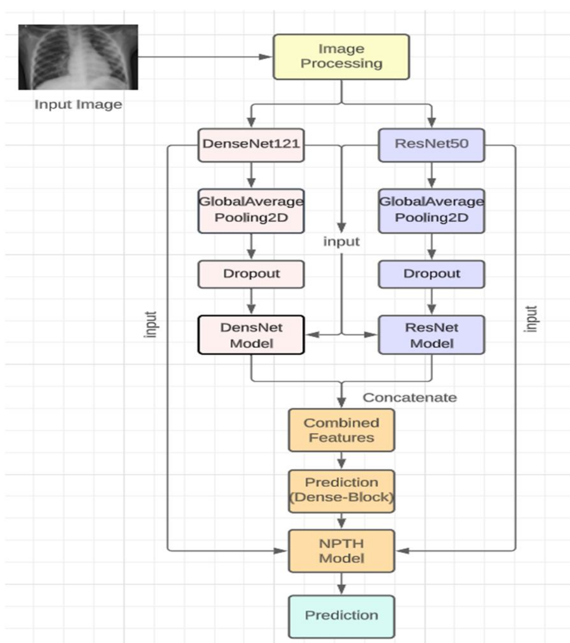

Fig.1: Model Architecture

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C. Model Training

A thorough training process was used to teach the suggested model for pneumonia identification discriminative patterns from chest X-ray pictures. During training, data augmentation techniques were used to provide changes to the training dataset and increase the generalizability of the model. These variations included rotating, shifting, shearing, zooming, and horizontal flipping.

The Adam optimizer was used to create the model, with a binary cross-entropy loss function and a learning rate of 0.001. The measurement metric for evaluation was accuracy. During training, callbacks such as early stopping, model checkpointing, and learning rate reduction were used. Model checkpointing and learning rate reduction altered the learning rate based on validation loss, whereas early stopping stopped training if no improvement in validation accuracy was seen.

The model was trained using a 32-person batch across 20 epochs. In order to produce data from the DenseNet121 and ResNet50 models, a combination generator technique was used, utilising the advantages of each pre-trained architecture.

The model's parameters were optimized during the training phase, and the pre-trained architectures were polished in order to improve the model's ability to detect pneumonia. The model was more robust and performed better as a result of the data augmentation, combined generator method, and smart training strategies.

D. Model Evaluation

Several models, including NPTH(this model), CNN, DenseNet, and RenseNet, were assessed in this study on pneumonia diagnosis using deep learning methods. They were evaluated using performance metrics like accuracy and false negative rate (FNR).

The best-performing model in this investigation was the NPTH algorithm, which stood out. Its high accuracy of 93.43% demonstrates that it can correctly identify occurrences and tell them apart from cases that aren't pneumonia. The NPTH algorithm's dependability and resilience in detecting pneumonia are demonstrated by this high level of accuracy.

Furthermore, the FNR score of 0.0426 for the NPTH method was exceptionally low. This indicates that it had a low rate of incorrectly classifying positive cases of pneumonia as negative, demonstrating a good sensitivity in correctly recognizing pneumonia. The NPTH model's low probability of false negatives is especially important in medical applications because failing to detect positive cases (in this case, pneumonia) could have detrimental effects on patients.

With its high accuracy and low FNR, the NPTH algorithm performs exceptionally, underscoring its potential for accurate pneumonia detection via deep learning. These findings imply that the NPTH algorithm can be viewed as a reliable and precise tool to aid healthcare providers in detecting pneumonia cases, thereby improving patient outcomes and increasing the effectiveness of healthcare delivery.

When choosing a deep learning model for pneumonia detection, academics and professionals should carefully take the advantages of the NPTH algorithm into account. It is an excellent option for this application because to its high accuracy and low false-negative rate, which lays a strong platform for future research and potential application in actual healthcare settings.

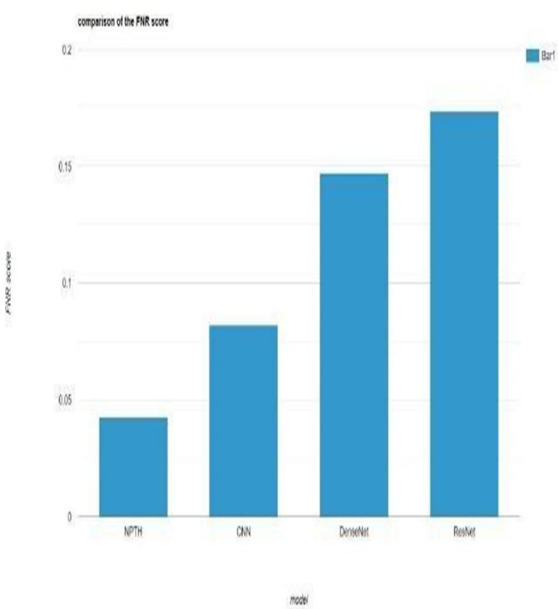

Fig.2: FNR Scores

E. High Level Design

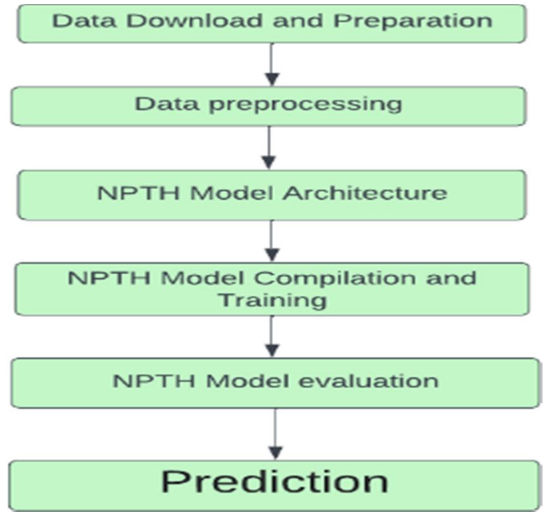

Fig.3: High Level Design

V. CONCLUSION

The research that was just presented used a hybrid architecture of the DenseNet121 and ResNet50 models to create a classification model for pneumonia identification from chest X-ray images. The model showed potential for pneumonia detection by achieving encouraging results in terms of accuracy and false negative score. The model demonstrated better generalization skills by utilizing transfer learning and data augmentation strategies.

In addition to the encouraging outcomes obtained in this study, a number of directions might be pursued in future research to improve the pneumonia detection model from chest X-ray pictures. The impact on the model's performance by fine-tuning the earlier layers in the DenseNet and ResNet models could be examined. Finally, it would be a worthwhile direction for future study to take into account the deployment of the established model in practical applications, such as integrating it into a web-based tool or creating an API for clinical use.

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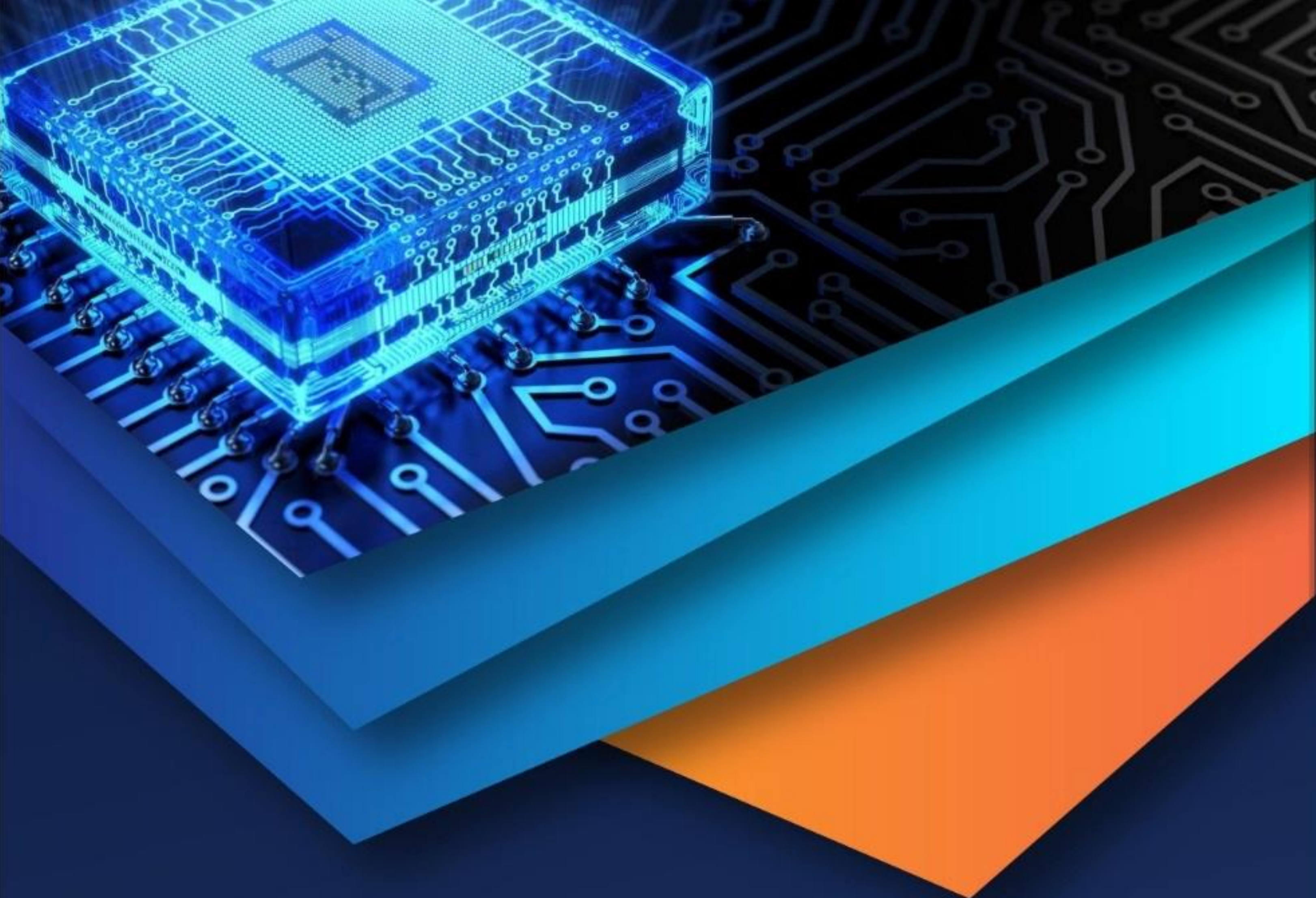

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