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IMAGE ENHANCEMENT IN LOW LIGHT CONDITIONS EMPLOYING ILLUMINATION MAP ESTIMATION

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Abstract-Low light images often exhibit colour distortion, fuzzy features, and poor contrast as a result of light scattering and attenuation in the water. In light of these issues, we present a low lightimage convolutional neural network (CNN) that uses structure decomposition for low lightimage improvement. In this case, theoretical analysis of the low lightimaging allows for the decomposition of the raw low lightimage into high-frequency and low-frequency components. Here, we provide a novel probabilistic approach to improving images by estimating both light and reflectance in the linear domain at the same time. Our results demonstrate that, compared to the logarithmic domain, the linear domain model is superior for representing background knowledge in order to estimate reflectance and illumination more accurately. The formulation is a maximum a posteriori (MAP) using previous knowledge about the lighting and the reflection. An asymmetrical multiplier

approach is used to compute illuminance and reflectance for the MAP issue. The experimental findings demonstrate the potential convergence rate of the suggested approach, as well as its good performance in

obtaining reflectance and illumination. The suggested approach produces findings that

are on par with or even superior to those obtained using other techniques of testing. The results of the ablation research prove that each component works as intended, and the results of the application tests show that the various approaches can produce high-quality photos in low light.

Keywords: LIME,CNN,Light image,HE,MAP.

1. INTRODUCTION

For the purpose of improving a picture, many enhancement strategies are utilised, such as grayscale modification, filtering, and Histogram Equalization (HE). One well-known method of improving images is called histogram equalisation. Because of how simple it is to implement, contrast enhancement quickly gained in popularity. In the second situation, generating artefacts that don't exist in the input picture can't be done without keeping the input image's brightness constant.

Although the output picture retains the original's brightness and contrast has been significantly improved, the results may not seem quite as natural as the original. The HE technique is predicated on the concept of gray-level remapping. Artifacts and artificial improvements are commonplace in HE systems. In order to combat these shortcomings, a variety of brightness maintaining approaches are used, all of which are discussed in the literature review. Several methods of improvement will be compared to one another.

There will be both subjective and objective criteria used in this evaluation. Objective parameters include the Peak signal-to-noise ratio (PSNR), the Mean squared error (MSE), the Normalized Absolute Error (NAE), the Normalized Correlation, the Error Color, and the Composite Peak Signal-to-Noise Ratio; subjective parameters include the perceived image quality and the processing time (CPSNR). The human visual system is much more advanced than the other four senses (hearing, touch, smell, and taste). A major portion of the human brain's daily routine is receiving and analysing pictures.

The visual cortex receives and processes more than 99% of all information entering the human brain. The data contained in a single photograph is astounding. A picture really is worth a thousand words, as Confucius once said. Of all the methods for digitally editing images, image enhancement is the most accessible and visually attractive. Image enhancement is often used to boost contrast in low-contrast images or to reveal hidden details in high-contrast images.

Output quality is diminished with any picture format conversion, including digitization. Among the many applications of digital image processing, picture augmentation is among the most accessible and visually attractive. Image enhancement methods are used to either draw attention to certain parts of a picture that could otherwise be lost in the background or to restore previously lost details. In Fig.1 we see a common kind of enhancement in which we boost the contrast of a picture and filter it to eliminate the noise so that "it appears nicer." Enhancement is a very nuanced area of image processing, so bear that in mind. These deteriorated photographs may be made more presentable via the use of enhancing methods.

As such, it represents a development of the standard Histogram Equalization method. It does this by adjusting the values in the intensity image I, so increasing the contrast of the pictures. It differs from HISTEQ in that it processes data in tiny sections (tiles) rather than the complete picture at once. The contrast of each tile is increased until the output region's histogram is almost identical to the one that was supplied. If you want to get rid of the artificially generated borders, you may join the neighbouring tiles using bilinear interpolation. In order to prevent the contrast from exaggerating any noise in the picture, it may be necessary to reduce the contrast in uniform regions.

Using the probability density function of grey levels, the original picture is divided into two halves of equal area in this innovative histogram equalisation method. After that, we adjust the contrast and brightness of each of the two individual photos. After the individual photos have been processed, they are combined to form the final image.

The technique is able to successfully boost visual information inside a picture while preventing a drastic change in the average brightness of the original image. So, it may be used in a video system without any intermediate steps. The input histogram is partitioned into many smaller histograms, each of which is balanced out by its lack of a dominant component. Each sub-histogram is then processed by HE, with the final enhanced picture allowing for a predetermined range of grayscale values. As computer vision technology has advanced, digital image processing systems have found increasing usage in a variety of settings, including but not limited to: manufacturing, surveillance, transportation, and remote sensing. Unfortunately, there are typically uncontrolled elements present throughout the process of picture capture, which leads to a wide range of image flaws. When there isn't enough light coming in from the outside, as might happen indoors, at night, or on overcast days, the light reflected off the object's surface can be feeble, leading to colour aberrations and noise that severely decrease the picture quality. A low-light picture suffers much more degradation during post-production processes including conversion, storage, transmission, and display. As its name suggests, "low light" describes an atmosphere in which the amount of available light is inadequate. Low-light photographs might be those that were taken in a dimly lit setting. To far, however, it has been hard to pin down the precise theoretical values that characterise a lowlight setting in real-world applications, and so no universal standard has emerged. So, each image-sensor producer has their own specifications; for instance, Hikvision often divides low-light conditions into three categories: dark level (0.01 Lux - 0.1 Lux), moonlight level (0.001 Lux - 0.01 Lux), and starry level (0.001 Lux - 0.1 Lux) (less than 0.001 Lux). Three low-luminance images and their corresponding grey histograms, where the X-axis shows the grayscale values and the Y-axis represents the number of pixels, illustrate the characteristics of images captured in such settings: low brightness, low contrast, a narrow grey range, colour distortion, and considerable noise. The absence of light causes the pictures' pixel values to be concentrated in the lower range, and it also reduces the grayscale variation between the colour image's channels. The difference between the darkest and lightest areas of the picture is rather minor. Details in the picture are hard to make out since the whole colour layer has irregularities and the edge information is lacking. The subjective visual impression of such pictures is severely diminished, and the usefulness of different visual systems is drastically reduced as a result of these qualities. Many hardware and software enhancements have been investigated by researchers to lessen the negative effects of video/image capture in low-light settings. One strategy involves enhancing the hardware of the picture capture system. One alternative is post-production processing of the resulting photos. The manufacturing process for low-illumination cameras is rigorous and the technology is complex because they use high-performance charge-coupled device (CCD) or complementary metal-oxide-semiconductor (CMOS) technology, professional low-light circuits, and filters to improve the imaging quality for lowlight-level imaging. A few professional low-light cameras from Sony, Photonis, SiOnyx, and Texas Instruments (TI), among others, have made it to market, but their prohibitive price tags have prevented them from becoming commonplace. Improving software algorithms is a viable option that provides a lot of leeway, and digital image processing research has long focused on finding methods to improve the quality of low-light films and photographs. To better the efficiency of imaging systems, research on enhancement algorithms for low-light pictures is crucial. Without a doubt, many vision-based approaches, like object recognition and tracking, rely on high-visibility pictures since they reveal distinct aspects of target situations. Yet, pictures taken in the dark are often blurry. For one thing, the visual quality of photographs produced in lowlight circumstances is just just enough. It also likely degrades the efficiency of algorithms that were built for more visible inputs. Several features, such as the paintings on the wall in the first instance, the distant field in the bottom-left corner in the third case, and the reflection on the floor in the final case, are virtually "hidden" in the gloom. There is an absolute need for low-light picture enhancement to unearth the hidden details. Recalling the visibility of dark parts is most likely to be achieved by directly enhancing the low-light picture. Nevertheless, this procedure introduces a new issue, in which relatively bright parts may get saturated and lose features. Avoiding the aforementioned issue is possible via histogram equalisation (HE) solutions, which work by ensuring that the output picture is inside the interval [0, 1]. It is also the goal of variational approaches to enhance HE performance by applying various regularisation factors on the histogram. Histogram mappings that emphasise substantial gray-level differences are the focus of contextual and variational contrast enhancement (CVC), whereas the work presented here seeks an enhanced layered difference representation of 2D histograms (LDR). Yet, in the wild, they over- or under-enhance by concentrating on contrast rather than using true illumination sources. Gamma correction, a nonlinear procedure on pictures, is another possible approach. One potential drawback is that the nonlinear operation of Gamma correction is performed on each pixel independently, without taking into account the relationship of a certain pixel to its neighbours. This can lead to improved results that are susceptible to visual inconsistencies with real-world scenes. That the (colour) picture may be broken down into its component parts—say, reflectance and illumination—is a fundamental tenet of Retinex theory. The method proposed in aims to improve contrast while maintaining the naturalness of illumination, in contrast to earlier Retinex-based attempts like single-scale Retinex (SSR) and multi-scale Retinex (MSR) [10], which treat the reflectance as the final enhanced result and therefore often look unnatural and frequently appear to be over-enhanced. Notwithstanding its ability to avoid over-enhancement, our experimental findings show that this technique is inferior to our own in terms of both efficiency and visual quality. A technique for adjusting the lighting was presented by Fu et al., which involves fusing various derivations of the first predicted illumination map (MF). As a whole, MF has been doing rather well. Yet, MF may fail to accurately render highly detailed areas owing to the blindness of its lighting system. Recent research by has presented a weighted variational model for estimating reflectance and illumination together in one pass (SRIE). Using the predicted reflectance and illumination, the lighting of the target picture may be improved. According to, flipped low-light photos resemble hazy snaps. Because of this finding, the developers of another method resorted to dehazing the inverted low-light photos. Dehazing produces artificial visuals, which are then reversed to get the final improved results. Subsequent work by Li et al., which also uses oversegmentation of the input picture followed by adaptive denoising of distinct segments, follows this technological path and improves visual quality even further. The aforementioned dehazing-like procedures may be effective, however the fundamental paradigm they are based on has no physical justification. The physical intuition behind our approach is much more apparent. Contribution We consider our approach to be part of the Retinex-based class of techniques, which seek to improve dim images by estimating their illumination maps. One key difference between our approach and more common Retinex-based methods is that we only estimate a single factor—in this case, the illumination—rather than both the reflectance and illumination. This reduces the size of the solution space and the amount of computation required to reach the desired result. First, the illumination map is built by determining the pixel's highest R, G, and B intensities. Then we use the light's structure to our advantage and create a more accurate light map. To address the refinement issue precisely, we provide an approach based on the Augmented Lagrangian Multiplier (ALM), and we also provide a sped-up solution that is meant to drastically cut down on the computational burden. We run experiments on a variety of difficult photos to demonstrate the benefits of our technology over existing state-of-the-art approaches.

High-resolution photos and videos are crucial for a wide variety of uses. Yet, not all pictures are high quality since they were taken in different lighting situations. Low dynamic range (low EV) occurs when a picture is acquired in low light, leading to a noticeable drop in image quality. It is difficult to make out individual features or textures because of how black the whole picture is. Hence, it's crucial to work on making low-light photos seem better.

The brightness and contrast of images have been the focus of several suggested algorithms. In order to get a more even distribution of pixels' values, histogram equalisation (HE) techniques [1, 2] are used. Techniques [3]–[7] based on the idea of retino-excitation postulate that a picture is the result of a dynamic interplay between light and dark. Pixel values are reset such that they conform to a normal distribution, and this is what the dehaze model [8] does.

All of these approaches are known as "conventional approaches." In the field of computer vision, convolutional neural networks (CNNs) have recently made significant strides. In the field of low-level image processing applications, CNN has achieved a number of firsts, including super resolution [9], image denoising [10], etc. To the best of our knowledge, however, there are no previously published publications that use CNN to perform low-light picture augmentation.

In this research, we use convolutional neural networks (CNNS) to improve photos taken in dim light. We propose a network that we call the Low-light Convolutional Neural Network (LLCNN). It learns to filter photographs acquired in low light with various kernels, and then combines these filtered images with multiscale feature maps to create improved images that seem like they were shot in normal lighting while preserving the original features and textures. In addition, we have included SSIM loss into our LLCNN for more precise texture reconstruction. By comparing our findings with those of other approaches, we show that our technique provides the most improvement over the state-of-the-art for low-light images.

Increasing Picture Quality in Dim Light: There are typically three types of techniques used to improve pictures taken in dim light. While using HE techniques, the pixel values are kept in relation to one another and are normalised as much as possible. By subdividing the histogram into many sections, dynamic histogram equalisation (DHE) [1] may apply HE processing to each of the histogram's constituent portions independently. The goal of contrast limited adaptive histogram equalisation (CLAHE) [2] is to adaptively restrict the level at which HE's contrast enhancement effect is applied. Details in shadowed regions are sometimes not adequately improved, and the colour cast issue is exacerbated when using these HE techniques. Methods based on the principle of retinoscopes may be used to improve an image by calculating its illumination and then discarding the results that don't add anything to the picture. Common examples of this technique's use include single scale retinex (SSR) [3], multiscale retinex (MSR) [4], and multiscale retinex with colour restoration (MSRCR) [5]. A few innovative techniques (SRIE [6], LIME [7]) have been presented to improve low-light photos by estimating illumination maps and reflectance. These techniques often result in significant colour distortion. Low-light photos are inverted before being processed using a dehaze approach using methods based on a dehaze model. To improve photographs with insufficient lighting, see [8]. Nevertheless, the improved photographs often seem too bright and the contrast is off.

Techniques of Deep Learning that are Analogous for Image Processing Success in low-level image processing applications has been driven by the availability of big datasets and the enhancement of calculating capabilities. When it comes to super resolution, VDSR [9] employs VGG filters and twenty convolutional layers to get remarkable outcomes. DnCNN [10] produces greater PSNR than conventional image denoising algorithms by using a network structure similar to that of VDSR and by adding batch normalisation layers following convolutional layers. It seems that LLNet [11] is the sole technique that uses deep neural networks to improve low-light photos. This network is a non-convolutional variation of a popular neural network architecture known as the stacked-sparse denoisingautoencoder. To create the effect of low lighting, a nonlinear process is used to darken photographs of the real world. All of these pictures will be used as a reference for future training. Low-light photos may be improved by the network after training.

Residual Knowledge and Inception's Module System C. As compared to shallower networks, deep ones perform better in many computer vision tasks. Nevertheless, as the number of stacked convolutional layers increases in depth, the network will run into the critical issue of vanishing gradients, which will hinder convergence as training progresses. Several layers of varying depths are linked together in inception modules [12], with each layer's output data being combined into a single vector. In 2014's ImageNet Large-Scale Visual Recognition Competition, GoogLeNet used inception modules to win the competition for classification and detection (ILSVRC14). The concept of residual learning [13] has also been presented as a solution. By using shortcut connections, deep residual nets may be optimised with more ease, and the resulting accuracy benefits can be more fully realised. At ILSVRC15, residual nets with 152 layers were quickly trained and placed first on various challenges.

1.1 Objective

The main objective of our project is,

1. To enhance the low light images effectively.
2. To implement the deep learning algorithm.
3. To enhance the overall performance for classification algorithms.

2. PROPOSED METHOD

The collection of photos used in this system is retrieved from a central source. After that, we may proceed with the picture pre-processing step's implementation. To do this, we must adjust the white balance and use history equalisation to boost the picture quality. The next step is to put a deep learning algorithm, such a Convolutional Neural Network, into action (CNN). The fidelity, confusion matrix, and ROC curve are all shown experimentally. Using these methods to improve the input image's quality is the last step. In this study, we suggest a convolutional neural network–based approach to improving images with poor lighting. In order to circumvent the gradient vanishing issue, we develop a specialised module that makes use of multiscale feature maps. Our model is trained using SSIM loss, which helps to keep picture textures intact as much as possible. Our approach may be used to adaptively improve the contrast in low-light photos. The results show that our CNN-based approach is superior to existing contrast enhancement techniques.

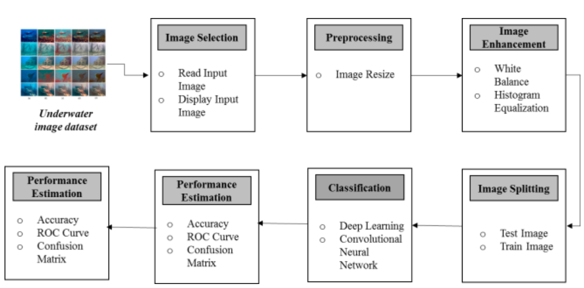


Fig1: System Architecture

2.1 MODULES:

1. Input image
2. Preprocessing
3. Image Enhancement
4. Image splitting
5. Classification
6. Performance Estimation

2.2 MODULES DESCRIPTION:

2.2.1: IMAGE SELECTION:

Low-light picture dataset is used as an input parameter. The information is retrieved from a central database. The input data set is a collection of images in the.png and.jpg formats. The imread() function is used to read or load the input image. The picture quality is improved by using the supplied image. The Tkinter file dialogue box is utilized in our method to pick the source picture.

2.2.2: IMAGE PREPROCESSING:

Image resizing and grayscale conversion are both necessary steps in our procedure. Using an image's resize() function with a two-integer tuple input that specifies the new width and height of the picture does this. Without altering the original picture, this method produces a new one with the updated proportions.

2.2.3IMAGE ENHANCEMENT:

White balancing and histogram equalization are two processes that must be included into our workflow. In photography, white balance (WB) refers to the technique of correcting for erroneous colour casts so that subjects that seem white in real life also appear white in your photographs. Color temperature, or the relative warmth or coolness of white light, is an important factor to consider when adjusting the white balance of a camera. Histogram Normalization: Image contrast may be improved using a method called histogram equalization. Often, this technique is used to boost the overall contrast of a large number of photos, which is particularly helpful when the image's useable information is represented by low-to-medium contrast values.

2.2.4: IMAGE SPLITTING:

When it comes to machine learning, data are essential for the learning process to succeed. The effectiveness of an algorithm can only be gauged via the collection and analysis of both training and test data. Seventy percent of the input dataset was used for training, while the remaining thirty percent was used for testing. The term "data splitting" refers to the practise of dividing a dataset into two distinct halves, often for use in a cross-validator setting. The data is split in half, with one half utilized to create a prediction model and the other half for testing. The evaluation of data mining models relies heavily on the creation of a separate training and testing collection of data. When data is split into training and testing sets, typically the larger set is used for training and the smaller set is used for testing.

2.2.5: CLASSIFICATION:

Implementing a machine learning method, such as a Convolutional Neural Network, is a necessary part of our procedure (CNN). CNN Convolutional neural networks (CNNs, or ConvNets) are a kind of deep neural network used extensively in the field of deep learning for the purpose of interpreting visual data. They are useful for NLP, image classification, medical image analysis, brain-computer interfaces, time series analysis, and visual recognition. In contrast to their multilayer perceptron predecessors, CNNs are regularised. Each neuron in one layer is typically linked to all neurons in the following layer in a multilayer perceptron.

2.2.6: RESULT GENERATION:

With this comprehensive categorization and forecasting, the Final Outcome will be derived. Certain indicators, such as

- Accuracy
- ROC Curve
- Confusion Matrix
- Then, we can enhance the input low light images.

3. RESULTS

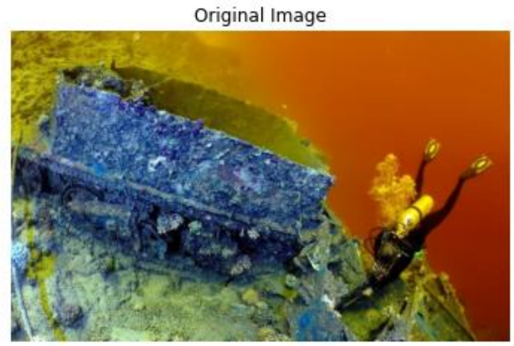


Fig2: Original Image

Fig3: White Balance Image

Fig4: Balanced Image

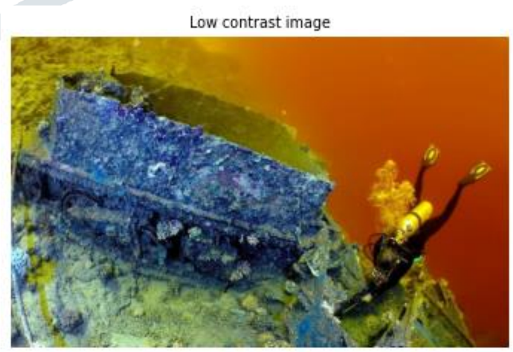


Fig5: Low Contrast Image

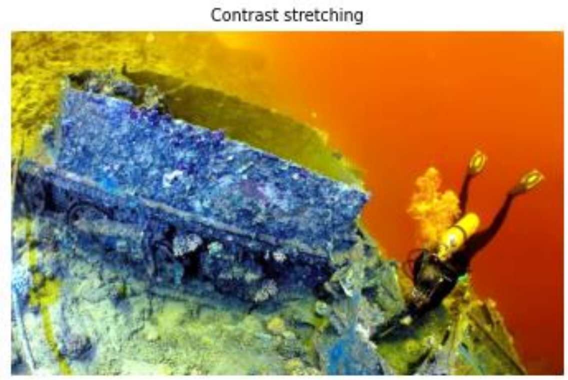


Fig6: Contrast Stretching Image

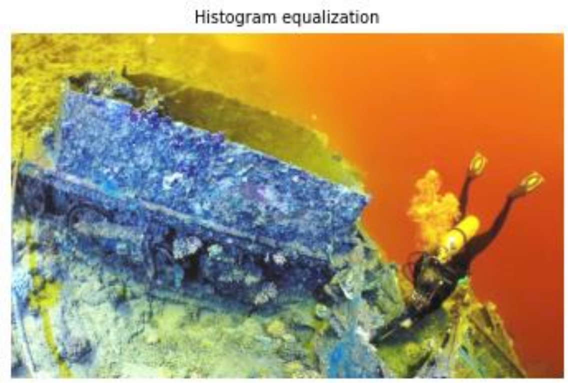
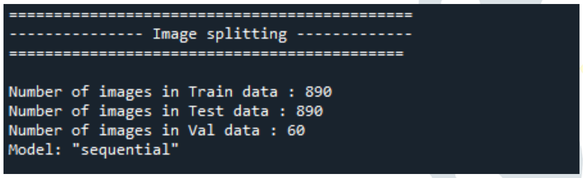


Fig7: Histogram Equalization



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-------------- Image splitting ------------
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Number of images in Train data : 890
Number of images in Test data : 890
Number of images in Val data : 60
Model: "sequential"
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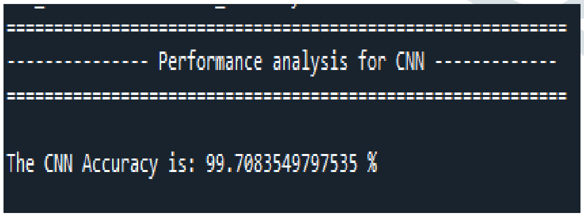
Fig8: Image Splitting



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-------------- Performance analysis for CNN ------------
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The CNN Accuracy is: 99.7083549797535 %
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Fig9: Performance Analysis for CNN

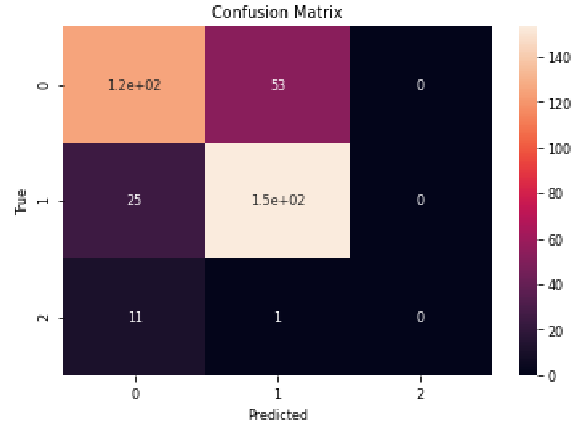

Fig10: Confusion Matrix

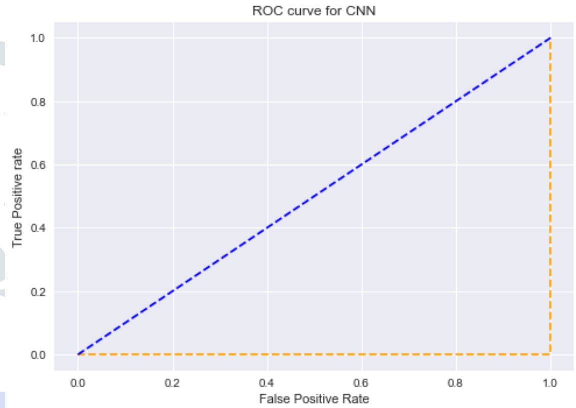

Fig11: ROC Curve for CNN

4. CONCLUSION & FUTURE SCOPE

The low-light photos used as a starting point were from a publicly available collection, we determined. To remedy this, we created picture enhancement methods including white balance and histogram equalisation. To this end, we have created a number of deep learning algorithms, including the Convolutional Neural Network (CNN). The results of the experiments showed that the picture quality might be improved by adjusting the white balance and the histogram. Then, we predict a number of performance parameters, including precision, recall, and ROC curve correctness.

For our next project, we want to merge two machine learning algorithms or two deep learning algorithms for enhanced performance and efficiency, or to create a hybrid approach to transfer learning.

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