CHAPTER 5

IMPACT OF LIGHT INTENSITY ON AUGMENTED REALITY RESPONSE TIME

5.1 INTRODUCTION

In this work it has been tried to combine the elements of real environment with the one that are created digitally. For the process of getting results realistically, it is essential to solve the intricate tasks of computer vision. Few examples of such activities include monitoring the real - time 3Dimensional objects and evaluating the light conditions of the scene.

The work has explained the concept of deep learning that was used for addressing the 2 complex problems with focus on both accurate and reliable as well. The possible solution to the problem introduced was to feed the system with the current active frame and a measure of object posture information according to the time prior timestep in sequence. Due to these reasons the network can correct the faults that arise during the process of closed loop tracking. Synthetic frames are created to track the items that enable feedback acquisition that may be as a measure of the current posture of object. The major techniques used in this work are shown in ***Figure 5.1***.

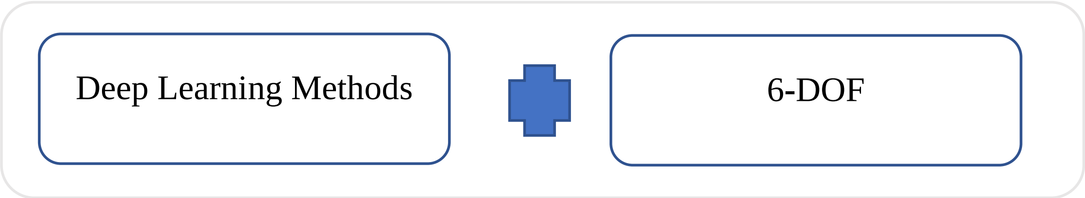


Figure 5.1 Major Techniques for Tracking

And so, our methods need a 3D rendering of something in addition to the instruction of tracking the devices using these models. Based on our research we assume that the this is the first work to use of Deep Learning for six DOF – Degrees of freedom, a dynamic item tracking but still it is not sure that we are the first one to use this.

In both cases, current developments are attained by the process of training the models of Deep convolution Neural Network on massive sets of data. The primary component of AR applications to provide a better experience is based on the effects of conditions of lighting. The lighting conditions have some great impact on retrieving the augmented information. The 2 use cases used in this work for studying the conditions of lighting.

AR for packaging of products in marketing. It will explain the usage of the product, visualize the catalogue and support details that are used for enhancing marketing strategy and to attract customers. Furthermore, the use scenario of AR is used for the learning process that explains the sub assembly machine.

5.2 PROBLEMS IDENTIFIED

It is difficult to infer the scene's lighting from a single image. The values of pixel of picture are based on many factors that includes the shape and substance of the scene, lighting, the camera that is used for capturing the picture and also any type of post processing that is performed on photograph. It is a poorly phrased inverse problem for separating one of these factors from the others.

Since there are several components that impacts the lighting of the picture, sometimes it is not easily noticed in pictures**.** Doing so from only a single, restricted field of the view of the photograph is quite a challenging task.

First, by presuming that the morphology that means the qualities of reflectance of scene is supplied that is measured using sensors of depth, reconstructed using other techniques or marked by any user, as well as second by applying any powerful low dimensional modelling upon illumination, this problem is mostly dealt with.

5.3 DESIGN AND STRUCTURE OF THE WORK

The major goal of the design and structure of network is described in the upcoming paragraphs. In this work detailed steps that are used in creating the instructional labels of pictures are given and they have been rendered such that they closely reflect actuality. This work also offers the loss measure used during superimposition-based training. We have provided an explanation for the demonstration on how these mechanisms work that is given in this present part.

The surrounding lights brightness is major significance in evolution of the software of applications of virtual reality that depends on the lighting circumstances. The process of design and its techniques for an app which uses augmented reality is broken out.

5.4 STAGES OF DEVELOPMENT TO TEST THE APPLICATION

The different stages of processes that are carried out in the proposed work from the stages of development to testing are shown in ***Figure 5.2.***

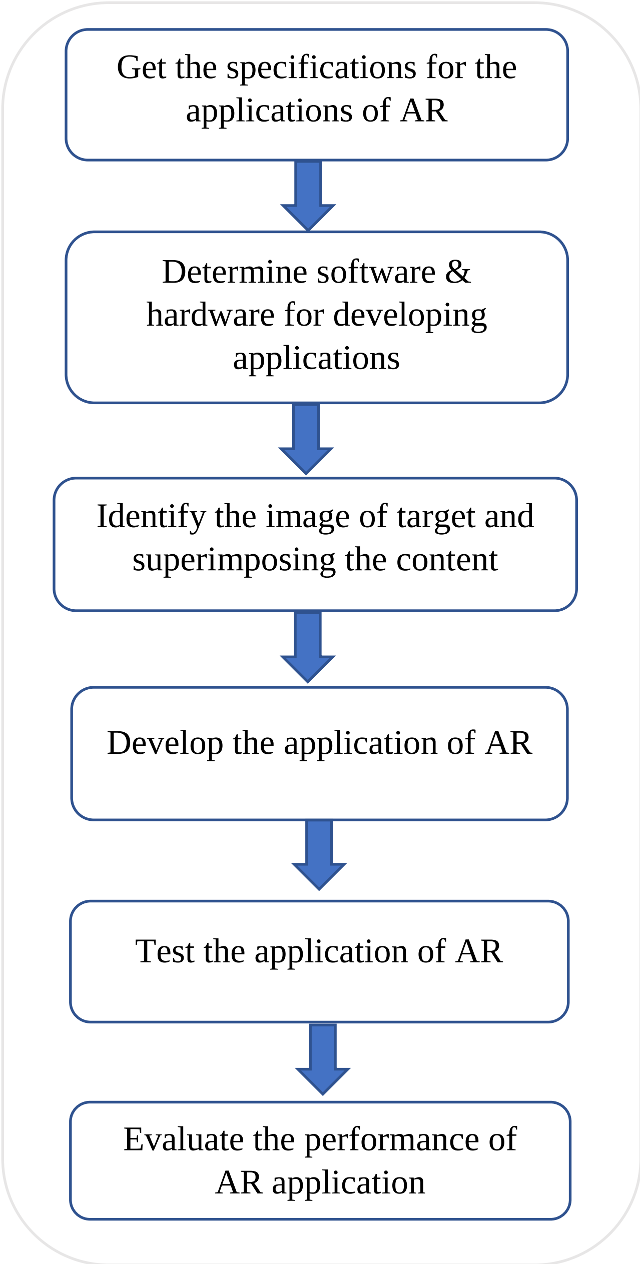


Figure 5.2 Process diagram for performance Evaluation of AR applications

To explain these processes, a DNN algorithm takes an input of 2 images they are

- One image shows the item that is displayed in its anticipated location that is as per the previous time stamps in the series of footage
- The other image shows the object as it is being viewed now.

Neural Network offers a direct result from 6 DOF that reflects the transition of posture between the 2 inputs. (3 for the process of translation and 3 for the process of rotation in Euler angles). For this work, a collection of photographs that are generated for the items according to the 3D hypothesis were used, for instructing the networks of computers. The first stage determines the need for using these augmented reality-based apps or the prerequisites that are involved in developing them.

For the process of developing an AR based application, the picture of target and the knowledge, the essential software and hardware should be determined and identified first. The marking of picture that is the target and the layered understanding is up to us to determine. Develop essential AR based apps with the help of marker and the data of overlay. And ensure that this software of AR works.

After developing these applications and ensuring that they are working now we have to put them into the smart phones, the programs based on AR which was created and test should be integrated to the smart phones. Testing the time of response will help in ensuring application performance.

5.4.1 Workflow Diagram of the Experimental Process

The workflow of performance of the application is depicted in ***Figure 5.3***. The process of developing the application starts with the following that are listed below

- The Target image is created.
- The image of target is created in both print and digital versions.
- The image of target is taken with various resolutions: they are high, medium and low
- Next step is to create an insight of overlay.
- The insight of overlay that is created are images and videos that are created for the targets.
- The applications of AR are developed with the help of the Unity Game Engine and Vuforia SDK.
- Evaluate the application to check whether it is functioning properly.
- Deploy the evaluated software of application in smart mobiles
- Get the results of test of performance by estimating the time of response of the superimposing insights with different intensity of lights of scanning that is in the

range of 46 lux and 423 lux and distance between marker (15cm) and the device of scanning.

- As per the response time that is obtained, plot the graph.

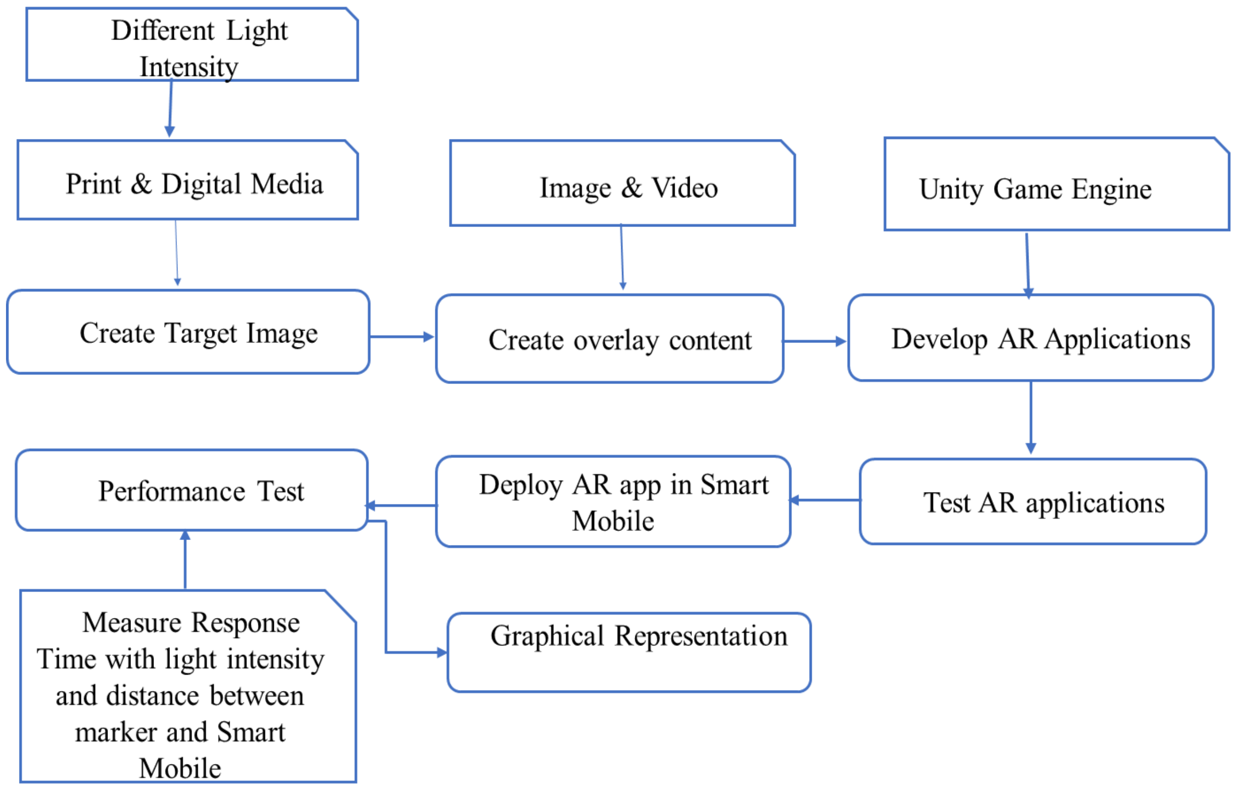


Figure 5.3 Workflow of performance testing of AR applications

5.4.2 CNN with 6DOF

In this proposed work, network of convolutional neural network is used, where the photographs or the images will be given as inputs, it produces an output of representation with low dimension of input via the convolutions downriver sequence and predictions of panoramic.

A big dataset that contains panorama for the process of training the algorithm was used. For the process of feeding a neural network, firstly we extract a regular picture from panorama, that presumes an algorithm of viewpoint camera that is sampled at random variables. While comparing the current techniques, our proposed real time historical 6-DOF approach of tracking the objects is more resilient for any kind of barriers. By the recasting of 6-DOF of monitoring as issue of challenge in the process of Deep Learning, this work has made a significant contribution (***Figure 5.4***).

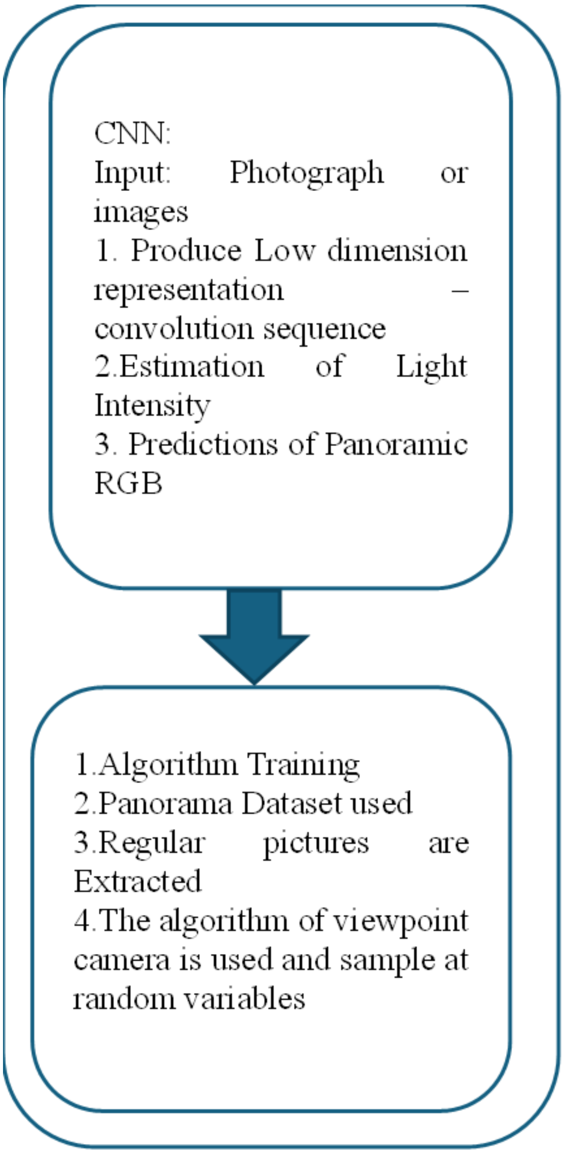


Figure 5.4 Process of CNN-6-DOF

There are 3 major advantages offered in this work. Firstly, the architecture of deep learning is able to being trained on huge volume of data that makes them resistant to commonly capture the flaws that includes variations in light and colour, images that are blurry and obscured.

Also, with a network that is compact enough, their implementations of GPU are so effective that they will be executed in real time on GPUs of mobile. Finally, and the most crucial, characteristics that are specific of objects can be learnt autonomously from the data, therefore no hand designed properties are required to be calculated.

This concept is so different from the existing works, where the characteristics are predetermined by hands. It is not that easier to implement a better CNN for the process of detecting. The tracking based on 6-DOF is shown in ***Figure 5.5.***

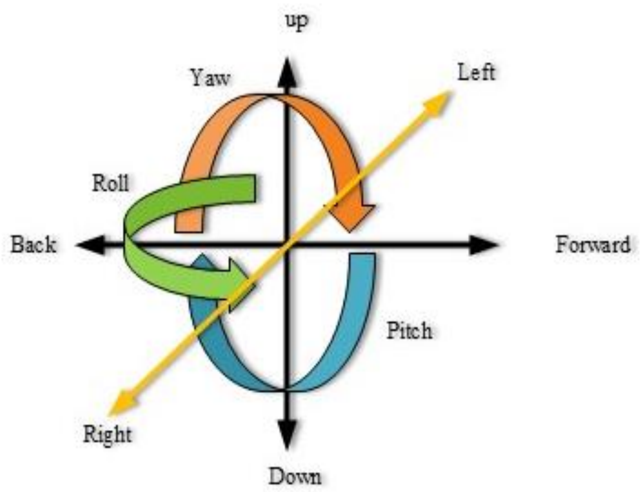


Figure 5.5 Tracking based on 6-DOF

Actually, the temporal trackers use 2 images or picture in time as consecutives. It is also assumed to be aware of the posture at preceding picture that differentiates it from the tracking that works by detection. One need to take only the present and previous frames into consideration for the process of training a deep network.

Though this model achieved lesser errors in outcome of predication on a conventional neural network population of test, where the population of test contains pairs of frames as input and stiff posture changes as target, it is unable to keep up with the sequence of multi frame.

Since this system is never taught to be self-correct, even the small mistakes will add up quickly and after few moments it will not be possible to keep them on track. As a replacement, you can offer the system with best guess at stance shift from the frameworks that are preceding.

In the results of tracking there will be higher errors due to the insufficiency of data for teaching the network accurately with larger level of representation. For addressing such issues, it was suggested to feed the network not just the current frame but also a projection of attitude of object that obtained from the prior timestamp in series. Due to this, a network will be able to fix its mistakes in closed loop tracking. For receiving a response or approximation of position of present moment of an object, an artificial picture for the item that is monitored in rendered.

And so, the model necessitates a prior rendering of 3D for every item and also the sensor is taught to be single kind of an object. For the 6 DOF temporal tracking of objects, it is believed that this work is the first to apply the method of deep learning.

To above mentioned points could be simplified as Reasons for using the Architecture of Deep Learning (DL)

- Ability to train on extensive volume of data
- These Deep Learning based architectures are resistant to many of the issues that have been mentioned in the challenges like variations in colour & light, Images that are Blurry and obscured
- Deep Learning is the most efficient on mobile GPUs as they offer real time execution under compact system network
- It is able to self the particular characteristics of objects

The main advantage of this model is that, previous models the pre-determined characteristics are not calculated with deep learning.

5.4.2.1 Challenges in Implementation of CNN for Object Detection

Temporal Trackers:

- Use of consecutive images
- Need of knowledge of posture from previous image

Training of Deep Network:

- Current frame and also previous frames are considered
- Obtaining minimal errors

Issue with Sequences of Multi-Frame:

- Accumulation of errors eventually
- Not able to self-correct

Advantages of Deep Learning with 6-DoF

- Feed Network
- Present Frame

- Attitude of the object is projected from the preceding timestep
- The mistakes in the process of closed loop tracking are fixed
- All the items are rendered in 3D.
- Sensors are trained on objects

This model has not been worked out with the use of CNN. Despite considering about construction, hyperparameters of variables to its possible to be taught on a produced information of picture about a particular item. Inception-ResNet-v2 is the base of our suggested application. It gets features from both Inception net Resnet, like consecutive and also concurrent information of convolution of information and will merge them.

This offers gradient propagation across the system of network that results in making the deep neural networks compliant to training. With its enhanced accuracy over the network Inception-v4, InceptionResNet-v2 became available for the process of classification of assignments involving 1000 various types of data. To make this work for the issues of regression, an overlay of fully interconnected blocks of MLP with only its extraction of characteristics was used. The weights that are learned during the process of training of recognition of objects on the datasets that are offered by an ImageNet that is used as the starting point for the method.

This will shorten the time it requires to get a handle on this problem. Since some of the filters may need to be retrained and some of the can be altered from ground up to fit it. The layer of dropout comes after the extraction of attributes. Each of the 4^{th} neuron in the before mentioned layer is turned off during the process of training, for a rate of total dropout of 0.25%. Five layers that are completely linked comes after the level of dropout. For 6 DOF estimation of posture, they cut total amount of neurons required from a 1000 to just 6.

These layers are adjusted as batches. As an operation of activation, PReLUs that is parametric Rectified Liner Unit was used. The HeNormal is applied to recommended weights. The confluence of trainer is enhanced over ReLU2 as well as is attained more quickly. 70% of data is used for the process of education and 20% for validating and 10% for evaluation. As already said, in this work evaluation on fake data was conducted with the help of the before mentioned 10% data that is taken for testing. Completely fresh sets of data are taken for evaluation on photographs of real world.

A generator will help in coordinating the use of data of training with a size of batch that contains 32 photos for each iteration, the algorithm, will load some random pictures and also the corresponding descriptions. There is no set of protocol for the sequence of images of training. But still, it is assumed that it follows a process of normal distribution during the process of training that owes to the data's random nature. In addition to this all the photos of the batch will undergo the mechanism of standardization along with the process of augmentation of data throughput the program. ***Table 5.1*** shows the network properties.

Table 5.1. Network properties

Property	Amount
Dimension of input	[299,299,3]
Dimension of output	[6]
films (total)	781
films (convolutional)	244
films (fully connected)	5
Strainers	76032
factors (total)	56986462
factors (trainable)	56921698
factors (non-trainable)	64764

5.4.2.2 Camera Pose Estimation

The location of c-Camera should be spaced out uniformly from central O. In these zero mean stance results in a chance of 50/50 across all of the dimensions. This problem can be addressed with predictable, concave polyhedrons like the icosahedron. And so, while using one of the existing methods it is possible to decompose the Polyhedron until the number of vertices will be equal to number of spots for the cameras that are required. The requirement for vantage points of camera that are uniformly spaced is satisfied by the process of projecting these coordinates to the rim of the sphere. Each of the angle of the point to the center point that is O is selected arbitrarily between 0 and S, that covers entire volume $[r_{\min}, r_{\max}]$ of S.

Orientations like the Roll, pitch and also the yaw can be employed for the purpose of describing the perspective of camera $(\phi_O, \theta_O, \psi_O)$ concerning the system of coordinate of O-space in which it is working. That is, complete reproduction. If there is a shift in angular velocity of round of rotation a $0° \leq \alpha \leq 360°$ point will minor shift in the direction that can have some major impact on estimating and the instruction of classroom are hampered by abrupt form of leap of 0 to 360 degrees. Due to these, employ the relational diagram $(\phi_C, \theta_C, \psi_C)$for becoming oriented.

Then began by pointing the lens to the globe's exact middle O that is given by c the coordinates. In addition to these, set upward vector of sensor as it faces the angle that is defined by up vector or the thing that is being observed and multiplied by the orientation of observing of camera. This will define an initial orientation of camera R-C that is relative to a local frame of reference C. Using the relative roll, diameter and yaw angles, as well as the local frame of reference C it is feasible $(\phi_C, \theta_C, \psi_C)$ for settling on a fixed angle on camera.

As a result, the matrix of entire rotation is $R = R_C \cdot R_{(\phi_C, \theta_C, \psi_C)}$. We have limited the angle of role to ϕ_C to a range of $\pm 45°$ as user-oriented AR based applications mostly makes the assumption of views of vertical camera. The pitch_Cand also yaw angle of camera to think about minimizing the view field ψ_C for falling within the pm half of the view field. This will result in a 60-degree view field θ_C, ψ_C that is being inside the margins $[-30°, +30°]$. That is the estimate to cases while above 50% of items are viewable in picture. This relative position can be used in future in conjunction with Rc for determining the position of absolute rotation.

Disadvantage of these type of depiction is its dependency on the camera's viewpoint. Thought the location of the sensor is estimated to be incorrect, even though their relative position is right, their exact alignment will be of error. The upside, however is the fact that the system has needs only to make an estimate inside a more limited value range ($\theta_C, \psi_C = [-30°, +30°]$ and $\phi_C = [-45°, +45°]$). If the item is still within the view field after motion, the values will be updated continuously.

For generating the tags of training and postures of camera for generating the pictures of training have used the data space which was described here. Thus, the work combines the sensor coordinate C of device for getting a posture of $p = (x, y, z, \phi_C, \theta_C, \psi_C)$ getting a complete form of 6-DOF from ancestor. Such kinds of posture are only obtained from the view points while somethings are partly in view. Each of the posture P which are generated is recorded as identifier in a file.

5.4.2.3 Image Rendering

For teaching the system, generate the pictures of RGB in an artificial way. First column of fourth figure shows a better illustration. We must strike balance between the size of the file of picture and as well as density of data. More data is available for measuring the measuring the purposed with larger photos. They also involve elements such as dust, scratches, residues of manufacturing, scratches and several other factors which are hard for reproducing the synthetic data. This will restrict the extension of the network. Maintain a standard size of picture of 299299 pixels throughout the process of designing.

With such level of detailing and view field $\varphi = \varphi_h = \varphi_v = 60°$. A 0.386 lateral shift cm for a each of the picture that is away 100 cm is conceivable theoretically

$$\frac{2 \cdot d(O,c) \cdot \tan(\varphi/2)}{w} = \frac{2 \cdot 100\text{cm} \cdot \tan(30°)}{299px} = 0.386 \frac{\text{cm}}{px} \qquad (5.1)$$

The 3D 6 model of unity is created for the visuals. Load the entire file of labelled data as (P) and cycle through each of the possible posture (p) of camera. For the process of getting more information on how the real-world photos are collected with real cameras. This is done for the final network to be more accurate to estimate the depth in pictures of real world. Constant improvement of data is considered for presentation.

The light is dispersed uniformly. It is important to account for the specular reflection. All the pictures have a translucent backdrop which will be covered throughout the learning as measure of stopgap for enhancing the information quality. Each of the picture is stretched with the help of Lanczos Filter and also generated at 16x frequency of target (4 times the dimension that is the height and width of each of the images). The techniques used in previous work is the randomized grid Super Sampling Anti Alienation is a technique that is used for anti-aliasing which will not alter the actual picture. At last, a picture is generated and saved on disks for all caption.

The mechanism of icosaheder decomposition is done with 400 division per edges for dealing with the increasing need of information for the constant upgrade of data. And so, n1.6106 pictures will make up the last image sets. Because the PNG is loss-free design of compressing, only require 40-80" " GB of total RAM for our applications. Before the instruction, the thing in the photos has lighting and also reflections that are baked on to it permanently. As such they are taken as consistent enhancement in statistics. The intensity of light and also the incidence angle will affect how things are seen, the self-shadows and the light that is reflected will also play its role.

For achieving this broad effect, the conditions of lighting of each of them representation of items are randomized independently. In the settings of industries, we will safely presume that the illumination will be constantly coming from above. For these reasons, use a vector which is random with even distribution for source of illumination, with the position of average having top-down, centre look at the items. For attaining the broad effect, the conditions of lighting of each of the representation of the item are randomized independently. In this work's setting of industries, we can safely presume that the illumination is coming in constantly from above. For such reason, use a vector which is random with an even distribution for the source of illumination, with average position having top-down, centre look at item.

5.4.2.4 Reflections

The intensity values of reflection sensors of the Unity3D are shuffled in a dynamic manner for generating many different types of reflections. Our digitized substances of database will define materials and also their fixed qualities (metallic and smoothness). In addition to the original image is randomly selected from collection COCO and also oriented for forming a cubic mapping of environment that is then pro-projected into the probe of reflection. This is attained using environmental mapping that generated reflection independent of its backdrop that is a new arbitrary backdrop is generated during the process of retraining. Next, investigate how this work is implemented in the next section.

5.5 IMPLEMENTATION AND DETAILS

In this section, the architecture of the system is discussed, that includes platforms, applications, use cases, experiments and conclusions.

5.5.1 Platform Description

The applications are developed with the help of the unity 3D engine and SDK Vuforia. At first the images of target are uploaded in the portal of target management of Vuforia. The display of interaction of user is designed with the help of Unity Engine and the database of target is imported. The content of overlay is stored in unity asset that is assigned to the images of target. Then the applications are converted into a deployable apk with the help of the SDK. ***Table 5.2*** shows the software and hardware specifications.

Table 5.2. Software and Hardware Specification

S.No	Software/Hardware	Specification
1	Unity 3D Engine	Unity 2018.4.36f1 (64-bit)
2	Vuforia SDK	Vuforia SDK Version 8.3.8
3	Visual Studio	Version 2017
4	Android SDK	Version 4.1 ‘Jelly Bean’
5	Light Luminous	LUX
6	Processor	Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz 2.50 GHz
7	Installed RAM	16.0 GB
8	Smart Device	Android device with camera

5.5.2 Prototypes of AR based Didactic System

There are 2 prototypes that are used in this work for developing the applications that are based on Augmented Reality. They are

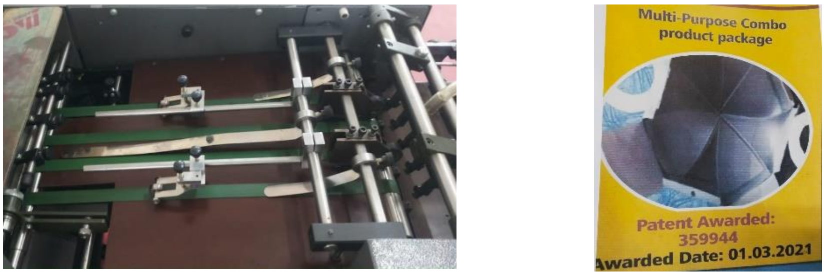
- Combo Box
- Offset Colt Machine.

There are 2 sets of images of target that are used in developing these applications with two different content of overlay that is the images and the video respectively. The video of overlay of the combo box will explain about their usage whereas the image of overlay of the offset machine will show various machine parts. The size of the video overlay is 40.7 MB and the size of the image is 123KB. The images of target of use case are of various resolution they are high, medium and low they are based on the quality of rating of images in the Vuforia portal of development. The light luminous of environment was computed using the application LUX, procured from the play store.

There are 2 types of images of target used in evaluating the performance of the application they are of digital form and the other is printed form. The images of target for the developed applications of AR are displayed in ***Figure 5.5a and 5.5b*** that showing the content of overlay for the images of target respectively

. **(a)** **(b)**

Figure 5.6 a. Target images (Combo box & offset machine) at 104 LUX b. overlay insight of the target (video & image)



(a) **(b)**

Figure 5.7 Target images at 423 LUX

The above ***Figure 5.7*** instances shows that our model can recover the source of light that are not apparent in shot by learning how to map from the appearance of prediction which makes it possible to relight the digital objects accurately and will also merge them as pictures. The application's Vuforia camera will track the image in marker, which compares it with the target that is stored in the device of database of Target, marker is recognised and insights of overlay are retrieved while the user scans the image of target with the help of the smart phones.

For the process of evaluating the model, user research are made where the subjects are prompted for selecting the more real ones of two photos feature the same re-illuminated virtual item under either of the ground truth or measured scenarios of lighting. A total of 41% of respondents have found our predicted image as real one, that is the result of ground truth is that there is a significant improvement in performance over the previous equipment. That have obtained a maximum of 27.7%. More data about this project along with its variations are suitable for using outside environments.

5.5.3 Experiment

In this work the application's performance is estimated with respect time of content overlay. The various content of overlay is displayed in videos and images. The reliability of this work is evaluated with various scanning intensity of light the distance between marker and the light source and the target image of type. (i.e. Digital or Printed Material)

There are various light intensity tracks used in this work they are

- Incandescent Light
- Fluorescent Light

When any obstruction is placed between the supply of light and also the object that needs to be illuminated, the flux of luminous will decrease to a 46 Lux from its higher intensity of 423 Lux. A program of light sensor LUX is used for assessing the level of luminance. The camera lens is 15cm away from objects that are being taken photographs. The two various forms of images of target that are used in digital and also the printed material. The major points of experiment process is explained in ***Figure 5.8***

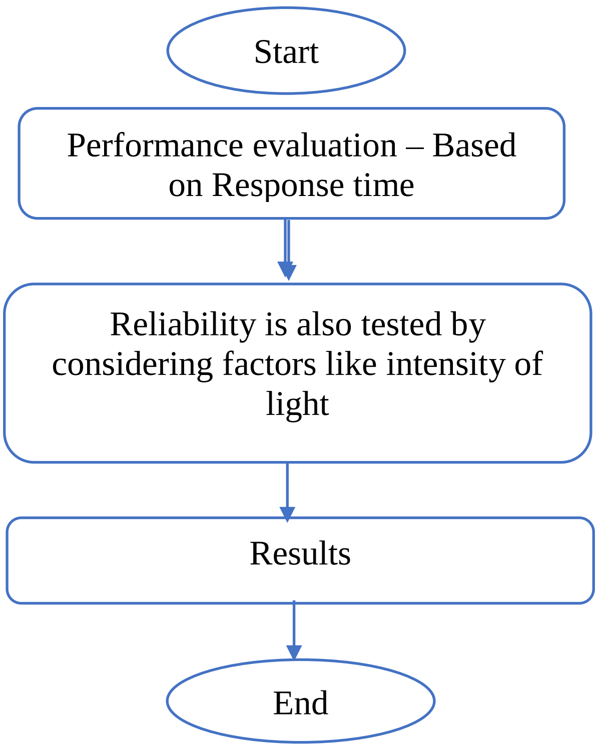


Figure 5.8 Experimentation Flow

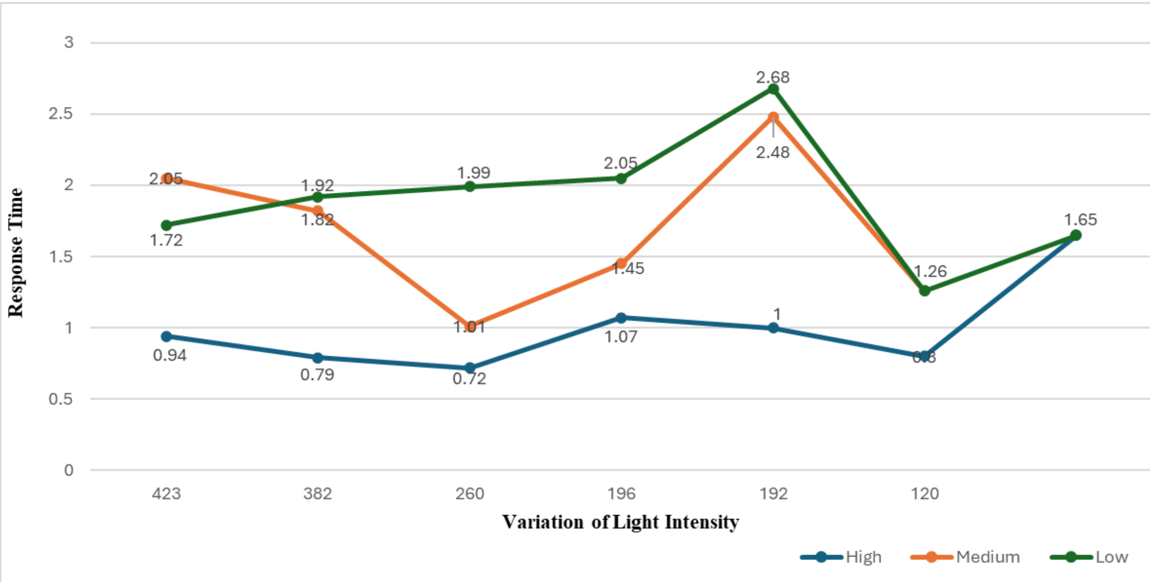
The performance of the application is evaluated based on many factors like

- Digital Image
- Printed Image
- Combo Box
- Offset
- Luminous Intensity
- Image Resolution
- Response time

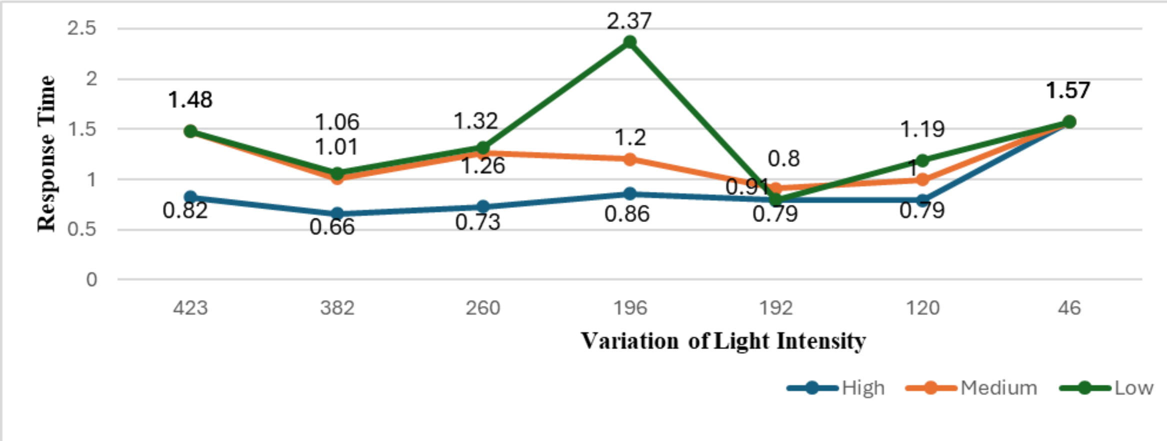
5.5.3.1 Digital Target Image

The time of response of application with the target of digital is shown in ***Figure 5.9***. The evaluation of how the applications performs is done with the help of taking the targets as digital images in various intensities of lights of scanning and distance between marker and the camera.

A. Varying Resolution of images of Target (High, Medium and Low) – Combo Box (Digital)



(a). Combo Box



(b). Offset

Figure 5.9 Response time of AR applications under varying resolution of Digital Target Image, different light intensity and distance

When the images of target are in digital form and they have various levels of intensity of light. The time of response of insight of overlay is estimated. It is found that the resolution of image of the target is higher the time of response will be optimal with different luminous of light. When the resolution of the image of target is of medium that is average then the time of response will be in increasing manner with change in luminous of light. As the luminous of light is decreasing the application's time of response will be higher.

When the target image's resolution is lower the time of response of insight's overlay and also no overlay is found at some lower intensity. It is found that if the intensity of light is high, the time of response of insight of overlay is optimal and when the intensity of light differs. The luminous light (L_T) is proportional to the time of response (T_R) of application's insight overlay.

5.4.3.2 Printed Target Image

The time of response of application with the printed image as target is shown in figure 6. The performance and efficiency of the application is evaluated with the help of printed images taken as targets in various intensities of light and distance between marker and the source of light. The images of printed target are captured to be of high, average and lower resolution. Their results are shown in ***Figure 5.10***

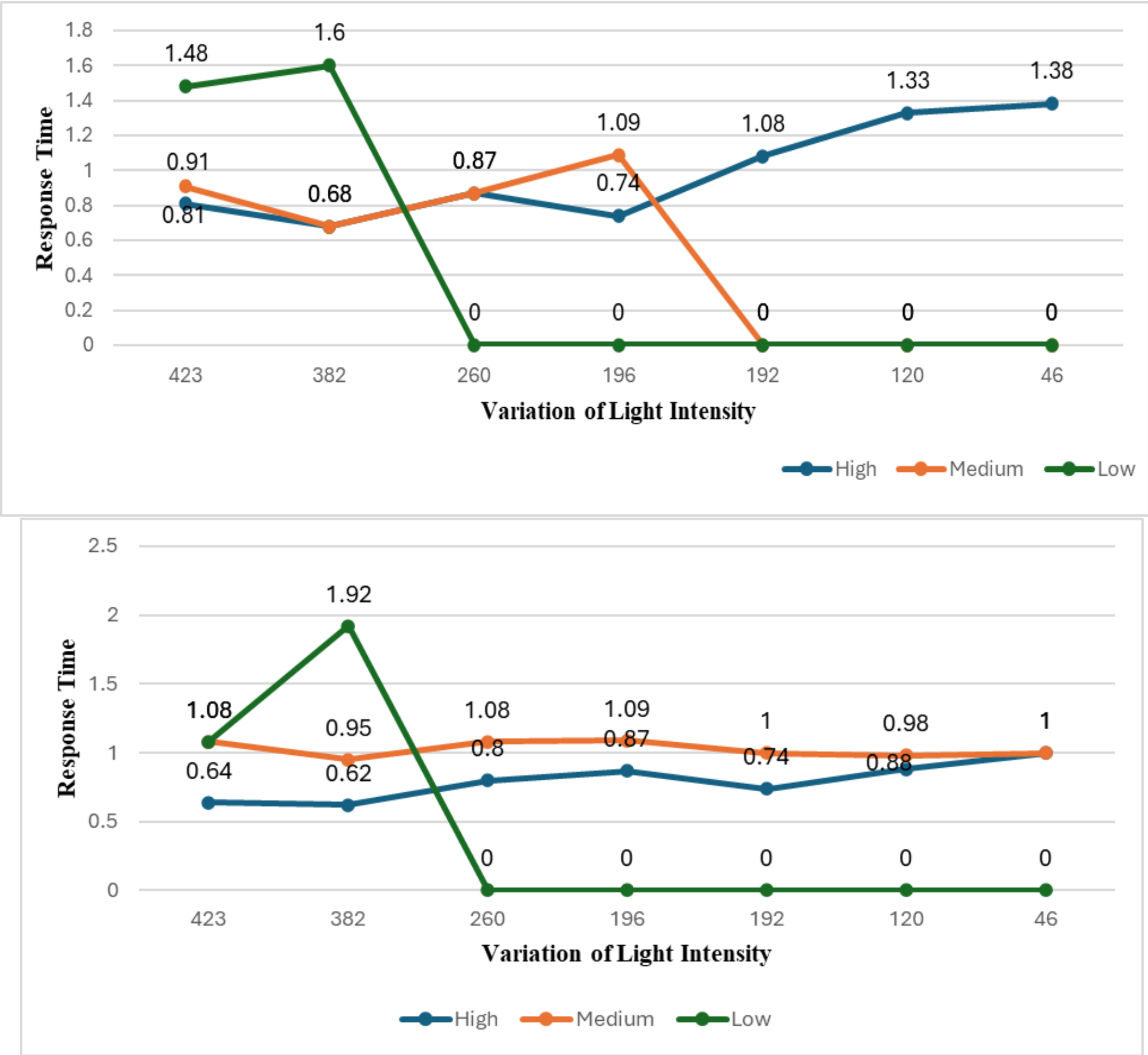


Figure 5.10 AR application's response time under different resolution of targets of printed images and different intensity of light and distance.

If the image of target is printed that too various intensity of light, the time of response of the insight of overlay is estimated. If the resolution of the image of target is high then the time of response will be optimal with different luminous of light. If the resolution of image of target is average then the time of response will increase with change in luminous of light. As the luminous of light is reducing the time of response of application will be higher.

It is found that if there is a high intensity in light, time of response of overlay insight will be optimal while the intensity of the light differs.If their low resolution of image of target, the time of response of overlay will increase a bit and there will be no overlay that is found at some lower intensity. The time of response is also dependent on the variants of color that is printed as targets. When there is a little deviation in color in the target that is printed, the time of response will vary based on that. The (L_T) light luminous will be proportional to the time of response (T_R) of the application's overlay insight.

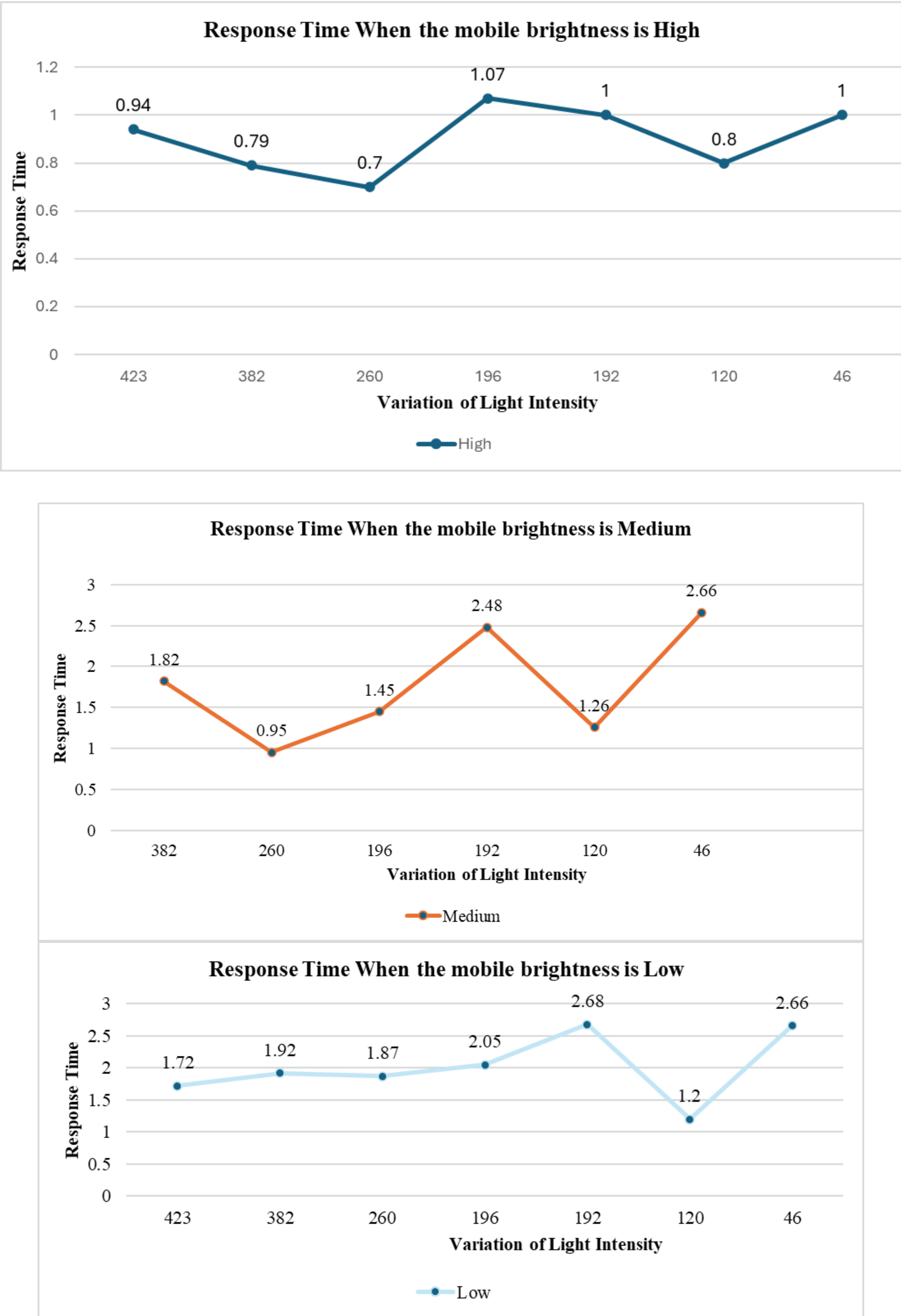
5.6 RESULTS AND DISCUSSION

With taking the digital images as target at 260 Lux and 46 Lux, the time of response of the application is higher and there is no overlay that is augmented at a much lower intensity. By the increase of brightness of mobiles there will be variations in time of response that is shown in ***Figure 5.11***.The response time is the critical feature that needs to be considered for any application because even though the results the time of response that is the time to takes to process will decide the significance of that particular application because though the results are efficient if the results if the response time is poor then the application will not preferred by users.

The time of response will be increased to some extent when the mobile's brightness is increased. The observations from the experiments are listed below, the application's performance will vary based on the target images that is of digital form or printed form of image.

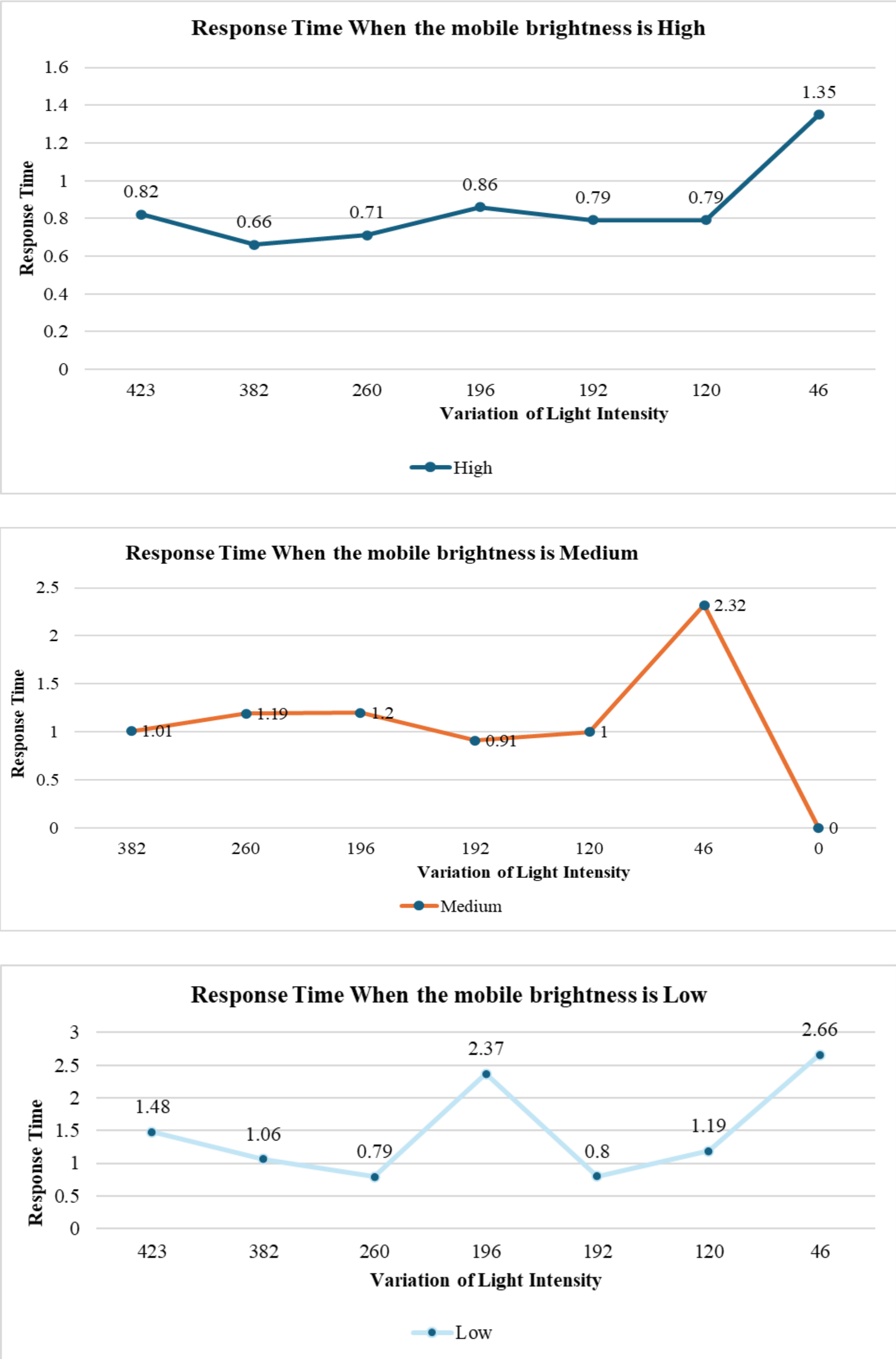
- The Application's performance will be different with digital marker showing lesser performance because of light's reflection on that target image while comparing to the printed marker.

- In addition to this the colors of markers have also some significant role in recognition of images. The gray scale markers recognition is faster than that of the RGB markers.



Response Time When the mobile brightness is High
Response Time
1.2
1
0.8
0.6
0.4
0.2
0
0.94
0.79
0.7
1.07
1
0.8
1
423
382
260
196
192
120
46
Variation of Light Intensity
High
Response Time When the mobile brightness is Medium
Response Time
3
2.5
2
1.5
1
0.5
0
1.82
0.95
1.45
2.48
1.26
2.66
382
260
196
192
120
46
Variation of Light Intensity
Medium
Response Time When the mobile brightness is Low
Response Time
3
2.5
2
1.5
1
0.5
0
1.72
1.92
1.87
2.05
2.68
1.2
2.66
423
382
260
196
192
120
46
Variation of Light Intensity
Low

(a) Combo Box



(b). Offset Machine

Figure 5.11 Mobile Brightness Impact on Response Time

5.7 SUMMARY

In this work, we have introduced the use of approach of deep learning to 2 difficult issues of analysis of visuals. The objects are tracked with the help of model 6-degrees of freedom and the brightness is also measured. In both the scenarios, the current outcomes are obtained by the process of training the deep convolutional neural network on huge volume of dataset. And so, it is expected that such technologies will lead to more apps that are based on Augmented Reality which will be able to respond to different conditions of lighting and environment. The markers of target are of 3 forms they are real objects, printed and digital objects. In this work, take 2 of these markers, that is the printed marker and digital marker for our experiment. The above experiment concludes that response time will be based on the intensity of light. The response time of the application is improved by increasing the smart phone's brightness instead of increasing the source of light. Finally, from the experiments it is found that the efficiency of printed markers is more effective than the digital markers because of reflections. While the efficiency of real objects as markers will depend on light's source, intensity, distance, reflection, texture and surface etc.