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# ANNEXURES

## ANNEXURE - I

### INSTITUTIONAL HUMAN ETHICS COMMITTEE



### *Avinashilingam*

Institute for Home Science and Higher Education for Women  
(Deemed to be university under Category 'A' by MHRD, Estd. u/s 3  
of UGC Act 1956) Re-accredited with 'A<sup>++</sup>' Grade by NAAC.  
Recognised by UGC Under Section 12 B  
Coimbatore- 641043, Tamil Nadu, India

05.01.2023

#### **Chairman**

Dr. Sudha Ramalingam  
Director – Research and Innovation  
Professor- Community Medicine,  
PSG Institute of Medical Sciences  
& Research, Coimbatore.

#### **Member Secretary**

Dr. A Thirumani Devi  
Professor  
Department of Food Science and  
Nutrition

#### **Members**

Mr. K. Arulmoli (Legal Expert)  
Dr. Subashini K. Sripathi  
Dr. A Saraswathy ( Medical Officer)  
Ms. D. Kavitha  
Dr. A R Sudamani Ramasamy  
Dr. G. Victoria Naomi  
Dr. Judith Justin  
Dr. Anitha Subash  
Dr. K. Sampath Rani

To  
Ms. Arthi, D.  
Department of Computer Science and Engineering  
Avinashilingam Institute for Home Science and  
Higher Education for Women  
Coimbatore- 641043


Dear Arthi,

Ref: Your proposal No. IHEC/22-23/E&ME-08 entitled  
"Effectiveness of Augmented Reality Mobile App for Different  
Domains" submitted for approval of IHEC on 21.11.2022.

The Institutional Human Ethics Committee of our University  
hereby grants approval to your research proposal No. IHEC/22-  
23/E&ME-08 entitled "Effectiveness of Augmented Reality Mobile  
App for Different Domains" submitted by you. The Approval number  
for the same is AUW/IHEC/E&ME-22-23/XPD-08.

We wish you all the best in your research endeavours.

Regards

  
Dr. A Thirumani Devi 5.1.23.  
Member Secretary



ANNEXURE - II

VALIDATION CERTIFICATE

Validation Certificate



To the Concerned Authorities,

This is to certify that **Ms. Aarthi D** has successfully developed the Augmented Reality application for Didactic System, which has been tested and validated by our organization. The application was evaluated on multiple parameters, including usability, content accuracy, technical performance, interactivity, and its effectiveness in enhancing the teaching–learning process.

- Functionally stable and user-friendly.
- Pedagogically effective in supporting classroom and laboratory teaching.
- Technically sound with smooth AR integration and interactive features.
- Valuable as a supplementary digital learning tool for students.

Based on the validation process, we hereby acknowledge that the Augmented Reality application for Didactic System meets the required educational and technical standards for classroom deployment and academic use.

We congratulate **Ms. Arthi D** for her effort and innovation in creating this application and recommend its usage for educational purposes.

Sincerely,

**S.Sabesh Kumar - CEO,  
SabyTheNoob**

A handwritten signature in black ink that reads "S. Sabesh Kumar".



[www.sabythenoob.com](http://www.sabythenoob.com)

**ANNEXURE - III**

**Questionaries for Survey**

Name

Age

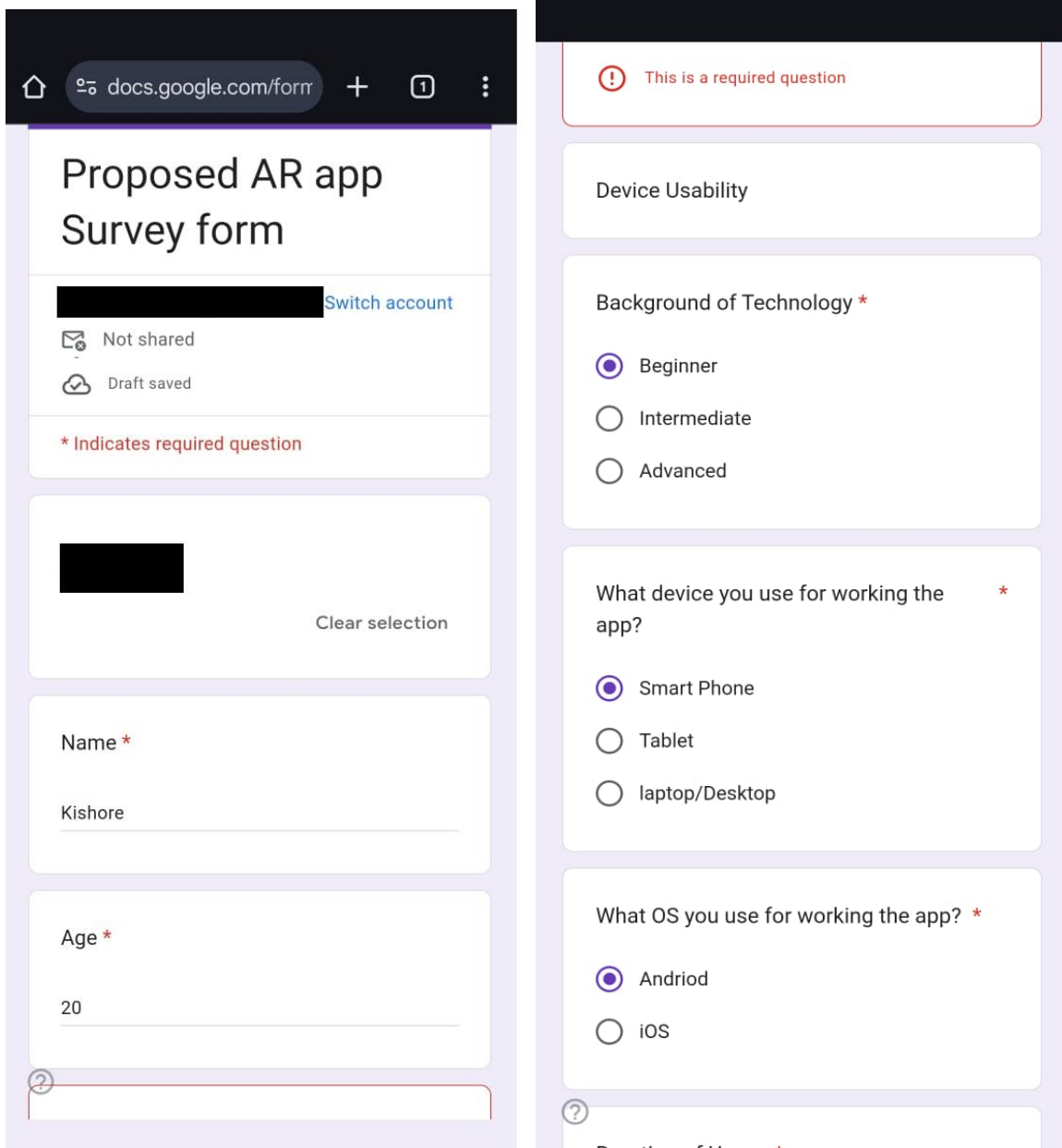
Gender

1. Background of Technology Knowledge: Beginner/ Intermediate/ Advanced
2. What device you use for working the app?: Mobile/ Tablet
3. What OS you use for working the app? iOS/ Android
4. Have you used the already existing app(Merge EDU, AR Flashcard, Assembly EDU, Quiver, JigSpace)? Yes/ No
5. Did you face any issue Existing application? Yes/ No
6. Feed back of existing app:

**For Proposed Prototype – AR Based Didactic System**

7. Duration of Usage: Less than 10 minutes/ 10-20 minutes/ 20-30 minutes
8. Where did you use the application? Class Room/ Lab/ Home
9. How easy was it to navigate the AR application?: Rating Scale 1-5
10. Was the interface intuitive and user-friendly? : Rating Scale 1-5
11. Rate Compared to traditional methods, how effective was this AR tool in enhancing your learning? : Rating Scale 1-5
12. How engaging did you find the AR content?: Rating Scale 1-5
13. Were the interactions (e.g., 3D models, clickable elements) responsive and meaningful?: Rating Scale 1-5
14. Rate the level of immersion (how real and absorbing it felt): Rating Scale 1-5
15. Did the app run smoothly without crashing or freezing? : Yes/ Occasionally Lagged/ Frequently Lagged/ Crashed Often
16. How compatible was it with your device? Yes/ No
17. Did the app load quickly and operate without delays? Yes/ No
18. Overall, how satisfied are you with the AR application? Rating Scale 1-5
19. Would you recommend this AR app to others? Yes/ No
20. Suggestions for improvement:

ANNEXURE IV  
SCREENSHOTS



Timestamp	Name	Age	Gender	Background of Technology	What device you use for working the app?	Duration of Usage
6/28/2024 12:20:08	Abishek J A	21	Male	Intermediate	Smart Phone	10-20 minutes
6/28/2024 12:22:05	B.Kishore	20	Male	Intermediate	laptop/Desktop	20-30 minutes
6/28/2024 12:33:29	Azeeza Maalin M	19	Female	Beginner	laptop/Desktop	10-20 minutes
6/28/2024 12:34:06	Asein.G	18	Female	Intermediate	laptop/Desktop	20-30 minutes
6/28/2024 12:34:17	Gladys Aniksha	18	Female	Advanced	laptop/Desktop	10-20 minutes
6/28/2024 12:35:11	B.Jaffar	19	Male	Intermediate	laptop/Desktop	20-30 minutes
6/28/2024 12:36:17	Janani	18	Female	Beginner	Smart Phone	20-30 minutes
6/28/2024 12:38:49	SYED Faazil.m	18	Male	Intermediate	Smart Phone	Less than 10 minutes
6/28/2024 12:44:16	Prathyush Hariharan M F	22	Male	Intermediate	Smart Phone	10-20 minutes
6/28/2024 13:02:49	Aishwarya D	18	Female	Intermediate	Smart Phone	10-20 minutes



## Avinashilingam Institute for Home Science and Higher Education for Women

(Deemed to be University Estd. u/s 3 of UGC Act 1956, Category 'A' by MHRD  
Re-accredited with A++ Grade by NAAC. CGPA 3.65/4, Category I by UGC  
Coimbatore - 641 043, Tamil Nadu, India

### Appendix L2

#### (Item No 5 of Check List) Details of Research Publications

S.No	Article	Journal	Other Details Vol/No/Page No/ Year	Published in UGC- CARE / Scopus Indexed/ Web of Science
1	Impact of Luminous on Augmented Reality Response Time	Journal of Advanced Research in Applied Sciences and Engineering Technology.	Vol. 49, Issue No: 1 Page No: 95-101 Year: 2025.	Scopus Indexed.
2	Augmented Reality - Dixon Technical Education for Sustainable Industrial Practices and Environmental Awareness.	Journal of Environmental Protection and Ecology.	Vol: 26 Issue: 4 Page No: 1594- 1603 Year: 2025	Scopus Indexed.

\*Proof of list of Journals from Internet to be attached along with copies of reprints.

Scholar

: *[Signature]*

Supervisor

: *[Signature]*  
27/9/2025

Checked By:

*[Signature]*  
27/9/2025

HoD/Dean of Respective School



# Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:  
[https://semarakilmu.com.my/journals/index.php/applied\\_sciences\\_eng\\_tech/index](https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index)  
ISSN: 2462-1943



## Impact of Luminous on Augmented Reality Response Time

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Augmented reality; target; overlay; deep learning; tracking; lighting estimation

### ABSTRACT

The goal of augmented reality is to combine elements of the actual environment with digitally created ones. In order to get realistic results, it is necessary to solve complex computer vision challenges. Some examples of these tasks include monitoring genuine 3D objects and assessing the lighting conditions of a scene. In this brief work, we explain how deep learning may be used to handle these two difficult problems in a way that is both accurate and reliable. As a potential solution to this issue, we have come up with the idea of feeding the network not only the currently active frame but also an estimate of the object's posture based on the preceding timestep in the sequence. Because of this, the network is able to repair any faults that occurred throughout the closed loop tracking process. The creation of a synthetic frame of the tracked item allows for the acquisition of the feedback, which may be thought of as an estimate of the current object posture. As a result, our approach requires a 3D rendering of something along with instruction of the tracking device using this model. We think we're the first to use deep machine learning for 6-degrees-of-freedom (DOF) dynamic tracking of items, but we can't be sure. In both cases, the latest developments are achieved by training deep convolution neural network models on massive data sets.

## 1. Introduction

The Augmented Reality is the technology that augments the digital information over the real world while scanning the targets. The main component of augmented reality application for a good experience depends on effects of light conditions. The light conditions have a great effect on retrieval of augmented information. Two use cases have been used for the study on the light conditions. AR for product package in marketing. It explains the usage of the product, displays the catalogue and other information that is used for ease marketing and attracting customer. Next, use case is an AR for learning that explains the sub assembly of an Offset printing machine.

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## **2. Literature Review**

Augmented Reality is a technology that superimposes information such as 2D/3D content, image, video, animations, etc. over the real world. Light intensity plays a vital role in marker detection and displaying virtual objects over the real world. The performance of the augmented reality applications in mobile or Optical See-Through Head mounted displays, mostly rely on the light luminous of the environment. Visual coherence paves a path in achieving augmented reality experience by superimposing the visual contents on the particular location, shape of the virtual object and the interaction between the real and virtual object. This Section gives the background study on significant of luminous for AR under the following three categories (i) the performance analysis of peripherals with mobiles and OST-HMDs, (ii) interactive augmentation and environment shading-based virtual objects and (iii) advancements in AR & VR displays.

### *2.1 Performance Analysis of Peripherals with Mobile and OST-HMD*

A mobile based augmented reality peripheral (ARP) was developed to visualize the academic rooms such as laboratories, classrooms, departments, study rooms, corridor, seminar rooms, meeting rooms and administrative service rooms in 2D and 3D form with room plan as marker. The reliability performance of the mobile based augmented reality peripheral application was determined by performing various tests by setting various light intensity, distance between the marker object and the AR peripheral and occlusion. As the result of the reliability test, the ARP app was successful above 300 Lux, where it failed below 95 lux. The distance was optimal at 60cm and occlusion was good at 40% occlusion of the marker area.

On the other hand, marker detection on wrinkled, wet and dry markers failed [1]. The effect of light outside on the perceived sharpness of white and black pictures on Optical See-Through Heads Mounting Displays. The study was conducted in a range of ambient light intensities, from zero to 20,000 lux. When exposed to illumination levels in excess of 10,000 lux, both inside and out, they experience a significant reduction in contrast. Virtual material presented in hues other than white is going to achieved decreased contrast ratios than when the display was displaying complete white or all black. Therefore, OST-HMDs need further development as well as refining for use in outdoor settings with more intense illumination [2]

### *2.2 Interactive Augmentation and Environment Shading Based Virtual Object*

Utilizing ray-tracing to produce a variety of lifelike effects at interactivity or real-time frame rates, this excellent renderer as well as mixing technology for augmented reality is a game-changer. Effects like refraction, reflection, as well as caustics may be simulated using interactive ray-tracing technology in AR on a single PC. The visual consistency of virtual reality is improved by these renderer techniques. Render times for various effects at various sample rates were used as performance markers. It was determined how long it takes the computer to do various rendering tasks including photon emission, Kd-tree construction, and tracing rays with estimated density. Researchers claim that the technology can remain interactive even with sceneries including 855K rectangles, like the transparent smiling Buddha. As a result, the system is capable of producing interactive augmentation [3].

Furthermore, an augmented reality system that is capable of estimating the light luminous of the outdoor scene and applying light changes to the augmented object according to the outdoor luminous. Investigators have employed a shadow quantity approach, which incorporates the amount

of light Volume to evaluate the environment's shading in the scene as well as an enhanced challenge is illuminated consequently, image-based lighting to simulate the various light sources that reflect the scene, and Phong obscuring to simulate the sun's shading, allowing shadows to interact with its surroundings. The shade is derived from an environment map that represents the most recent light shifts in the scene, based on approximated local brightness characteristics. This allows the technology to instantly refresh the illumination of a simulated reality-based item depending on a picture [4].

### *2.3 Advancement in AR and VR Display*

Both virtual reality (VR) as well as additive reality (AR) is influencing the way we take in and respond to simulated data in many forms. Because of their ability to recreate the connections between CGI as well as the actual environment, they have attracted a lot of attention and work. In recent years, a number of cutting-edge designs have emerged, each with its own set of advantages. For example, tunable lenses may minimize VAC, polarizing materials can address space constraints, as well as freeform optics can expand the field of vision. Displays that combine VR and AR have significant scientific implications and several potential practical applications [5].

### *2.4 Research Problems*

It is difficult to infer the lighting of a scene from a single image. picture pixel values depend on several factors, including the scene's shape and substances, the lighting, the camera used to capture the picture, as well as any post-processing that was performed on the photograph. It's a poorly phrased inverse issue to separate one of those factors from others. Because numerous of the components that influence the picture's lighting is not immediately noticed in the picture (Figure 1), doing so from just a single, restricted field-of-view photograph is very challenging. First, by presuming that the scene's morphology (and/or reflectance qualities) is supplied (measured by depth sensors, reconstructed via other techniques, or marked by a user), as well as second, by enforcing powerful low-dimensional modeling upon the illumination, this issue is often dealt with.

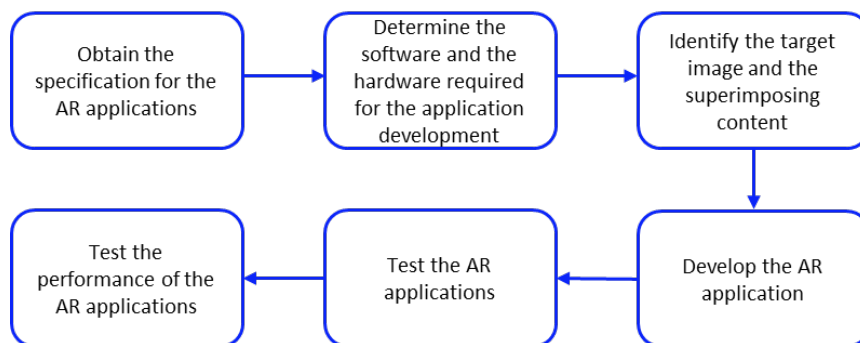
### *2.5 Proposed Work*

Our goal network's design and structure are described in the next paragraph. Here, we detail the steps used to create the instructional pictures' labels as well as render them such that they more closely reflect actuality. We then provide the loss measure utilized during superimposition-based training. A brief explanation of a demonstration wraps up the present part. The brightness of the surrounding light is a major factor in the evolution of virtual reality software. The time required to get overlay information from a virtual reality app varies depending on the circumstances of the lighting. The design process as well as technique for an app that uses augmented reality is broken out here.

## **3. Methodology**

Figure 1 depicts the different stages involved in developing and testing the performance of AR applications. In brief, its deep neural network algorithm takes in two images as inputs: one showing the item displayed in its expected location (based on the previous time stamps in the footage series), and the other showing the object as it is now being viewed. The neural network provides a direct result from the six degrees of freedom (DOF) reflecting the posture transition among the two inputs

(three for translation and three for rotations in Euler angles). We use a collection of computer-generated photographs of the item, based on its 3D hypothesis, to instruct the network of computers. The first stage is to determine why augmented reality apps are needed, or the prerequisites for constructing them. To create AR apps, a target picture and knowledge, the necessary software's and hardware must be identified. It's up to you to make the marking (target picture) as well as the layered understanding. Create the necessary augmented reality apps using marker and overlay data. Make sure the augmented reality software works. Put into use on intelligent mobile the augmented reality programs you have created as well as tested. Response times testing to ensure performance of the application.

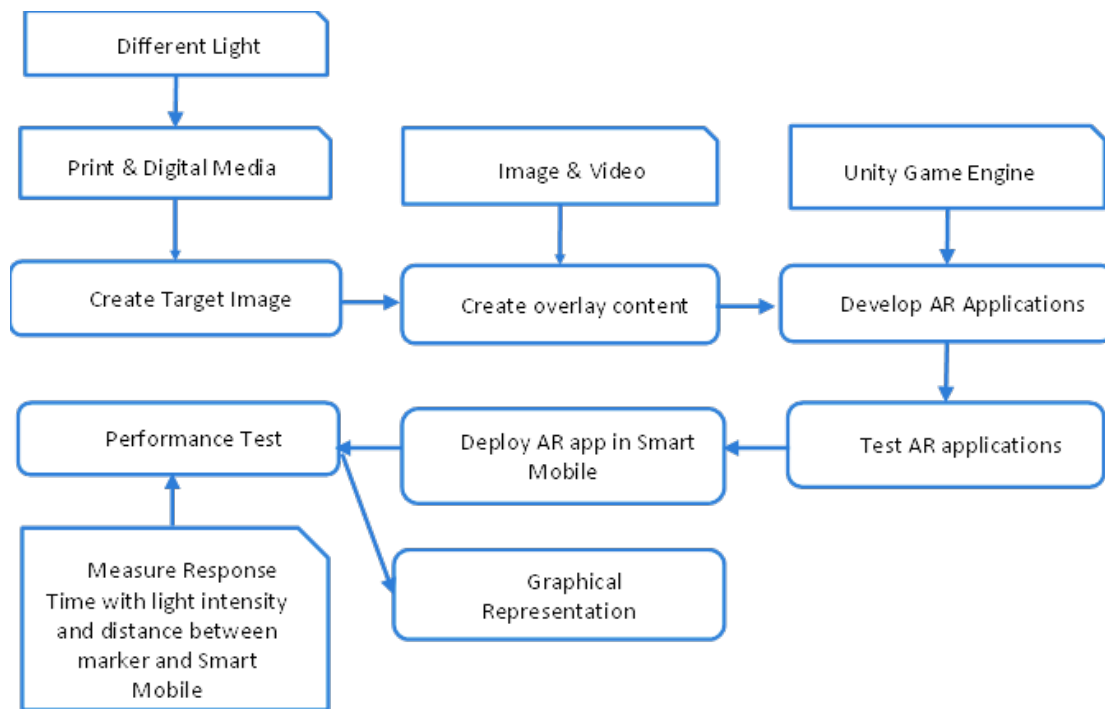


**Fig. 1.** Process diagram for performance testing of AR applications

### 3.1 Workflow Diagram

The workflow of the application performance is shown in Figure 2. The development of the application starts with

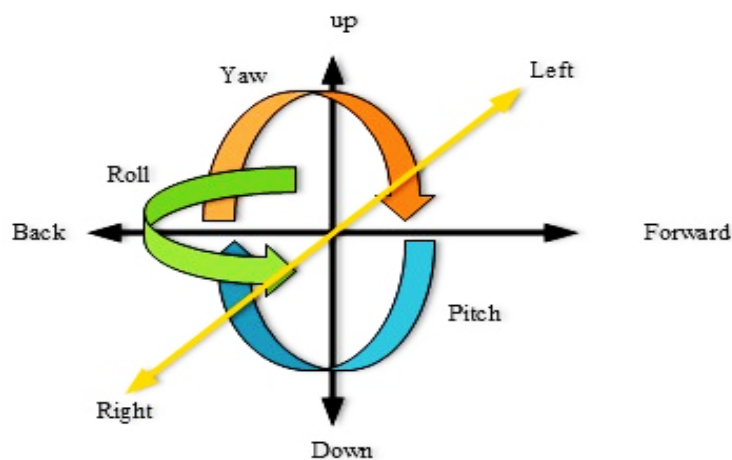
- i. The creation of the target image.
- ii. The target image created is both print and digital version.
- iii. The target image is taken with different resolution high, medium and low respectively.
- iv. The next step is creation of overlay insight.
- v. The overlay insight created is image and video for the created targets.
- vi. The AR applications are developed using Unity Game Engine and Vuforia SDK.
- vii. Test the application for its proper functionality.
- viii. Deploy the tested application software in the smart mobile.
- ix. Obtain the performance test result by measuring the response time of the superimposing insight with different scanning light intensity between 46 lux and 423 lux and distance between the marker (15cm) and the scanning device.
- x. Plot graph according to the response time observed and obtain the result.



**Fig. 2.** Workflow of performance testing of AR applications

### 3.2 CNN with 6DOF

Specifically, we utilize a network of convolutional neural networks that, given a photograph as inputs, generates a low-dimensional representation of the input through a sequence of convolutions downriver, and subsequently divides into two upfront extensions to perform, respectively: (1) light intensity estimates and (2) RGB panoramic predictions. We use a big dataset consisting of panorama to train the algorithm. To feed a neural network, we first extract a regular picture from a panorama, presuming a viewpoint camera algorithm with sampled at random variables. Compared to current state-of-the-art techniques, our real-time historical 6-DOF object tracking approach is more resilient to occlusions (Figure 3). By recasting 6-DOF monitoring as a challenge in deep learning, we have made an important contribution.



**Fig. 3.** DOF tracking in AR

There are three main advantages provided by this work. First, deep learning architectures are capable of being trained on massive volumes of information, making them resistant to common capture flaws including color and light variations, blurry images, and obscured subjects. Also, with a compact enough network, their GPU implementations are so efficient that they can be executed in real time on mobile GPUs. Finally, and most crucially, object-specific characteristics may be autonomously learnt from data, thus no hand-designed properties needed have been calculated. This differs from the majority of prior work, where computed predetermined characteristics by hand. It's not easy to implement a sophisticated convolutional neural network (CNN) for detection. Actually, the temporal trackers employ two images (pictures) consecutive in time. It also presupposes being aware of the thing's posture at the previous picture, which distinguishes it from detection-based tracking. One need only take the current and prior frames into account while training a deep network for that purpose.

Besides that, this approach achieves minimal errors in prediction on a "traditional" neural network test population (consisting of frame pairs as input and stiff posture changes as target), it is incapable of keeping up with multi-frame sequence. Since a system has never been taught to self-correct, even seemingly little mistakes eventually add up. quickly, and after a few moments, it becomes impossible to keep track of it. As an alternative, you may provide the system with your best guess at the stance shift from the preceding frames. High errors in tracking result because this data is insufficient to teach a network accurate large-level representation. To address this issue, we suggest feeding the network not just the present frame but also a projection of an object's attitude retrieved from the preceding timestep in the series. Because of this, a network can fix closed-loop tracking mistakes. To receive a response or approximation of the present moment position of an object, an artificial picture of the monitored item is rendered. As a result, our method necessitates an a priori 3D rendering for every item, as well as the sensor is taught on a single kind of object. For 6-degrees-of-freedom (DOF) temporal object tracking, we believe that we're the initial to apply deep learning.

Our approach would not work without the CNN. Despite caring about the construction, variables, or hyperparameters to it's possible to be taught on generated picture information about an item. Inception-ResNet-v2 [6] serves as the foundation for our application. It takes features from both the Inception net and Resnet, such as consecutive as well as concurrent convolutional layers of information, and merges them. This facilitates gradient propagation across the network, which in turn makes deep networks amenable to training. With its improved accuracy over the Inception-v4 the network, InceptionResNet-v2 became available for classification assignments involving 1000 different types of data.

To make it work for this regression issue, we overlay a fully interconnected MLP (multilayer perceptron) blocks with only its characteristic extraction (see Figure 2). The weights learned during object recognition training on the dataset provided by ImageNet are used as the starting point for the model. This significantly shortens the time it takes to get a handle on our issue, since certain filters might need to be retrained and some may be modified from the ground up to fit it.

The dropout layer comes after the attribute extraction. Every fourth neuron in the aforementioned layer is turned off during training, for a total dropout rate of 0.25. Five completely linked layers come after a dropout level. For 6-dof posture estimation, they cut the total amount of neurons needed from a thousand to only six. The layers have been adjusted in batches. As activation operate, we utilize Parametric Rectified Linear Units (PReLU). HeNormal applied the recommended weights. Trainer confluence is improved over ReLU2 as well as is achieved more quickly.

Table 1 summarizes the finished network's characteristics. There are fewer variables in this network compared to AlexNet (60 million) as well as VGG16 (138 million). It takes up 654MB of storage space on disc and is formatted as HDF5 (Hierarchical Information Format).

Seventy percent of the information is used for education, twenty percent for validation, and ten percent for testing. We conduct an assessment on fake information using a portion from the 10% test data. Completely fresh sets of information are employed for assessments on real-world photographs.

A generator coordinates the use of the training data. With a batch size of 32 photos each epoch, the algorithm loads at random pictures as well as the corresponding descriptions. There is no set protocol for the sequence of training images. However, we may infer that it will follow a normal distribution during training owing to the randomized nature of the data. In addition, all batch photos undergo standardization along with information augmentation through the program.

**Table 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

### 3.3 Camera Pose Estimation

The c-camera locations must be uniformly spaced out from the central O. The zero-mean stance results in a 50/50 chance across all dimensions. This issue may be addressed with a predictable, concave polyhedrons (such as an icosahedron). So, using the same approach as in [7], we decompose a polyhedron until the number of vertices is equal to the number of spots for the cameras we need. Our need for uniformly spaced camera vantage points is met by projecting those coordinates to the sphere's rim. Each point's angle to the central point O is arbitrarily chosen between 0 as well as S, covering S's whole volume  $[r_{\min}, r_{\max}]$ .

Roll, pitch, as well as yaw orientations might be used to describe the camera's perspective  $(\phi_o, \theta_o, \psi_o)$  in terms of the coordinate system of the O-space we're working in. Complete reproduction is what we mean here. As the angular velocity of rotation around a point  $0^\circ \leq \alpha \leq 360^\circ$  minor shifts in direction may have major effects on estimating, and classroom instruction can be hampered by the abrupt leap from 0 to  $360^\circ$ . Because of this, we use a relational diagram  $(\phi_c, \theta_c, \psi_c)$  in order to become oriented.

We start by pointing the lens to the exact middle of the globe, O, which is given by the coordinates c. In addition, we set the sensor's upward vector such that it faces in an angle defined by the up vector or the thing being observed multiplied by the camera's observing orientation. This defines an initial camera orientation  $R_C$  relative to a local reference frame C. With the help of our relative roll, diameter, as well as yaw angles as well as the local reference frame C, it's possible  $(\phi_c, \theta_c, \psi_c)$  to settle on a fixed camera angle. Consequently, the whole rotation matrix is  $R = R_C \cdot R_{(\phi_c, \theta_c, \psi_c)}$ . We limit the roll angle  $\phi_c$  to a range of  $\pm 45^\circ$ , as user-focused augmented reality apps often make the

assumption of vertical camera views. We restrict the pitch  $\psi_C$  as well as yaw angle of the camera in order to think about reducing our field of view (FOV)  $\psi_C$  to fall inside of pm half the field of view. This will lead to a  $60^\circ$  field of view  $\theta_C, \psi_C$  being inside the margins  $[-30^\circ, +30^\circ]$ . This restricts the estimate to cases when more than 50% of the item is viewable in the picture. This relative position  $(\phi_C, \theta_C, \psi_C)$  may be used in the future in conjunction with  $R_c$  to determine a position's absolute rotation.

The disadvantage of this kind of depiction is its reliance on the viewpoint of the camera. though the sensor's location is estimated incorrectly, even though its relative position is right, the exact alignment will be erroneous. The upside, nevertheless, is the fact the system we have requires only to make estimates inside a more limited range of values. (e.g.  $\theta_C, \psi_C = [-30^\circ, +30^\circ]$  and  $\phi_C = [-45^\circ, +45^\circ]$ ). If the item is still inside the field of view after the motion, the values are continuously updated.

To generate training tags and cameras postures for producing synthetic training pictures, we employ the data space described here. Therefore, we combine the c coordinate of the sensor with the orientation of the device to get a posture  $p = (x, y, z, \phi_C, \theta_C, \psi_C)$  obtaining a complete 6-dof from an ancestor. These types of postures can only be achieved from viewpoints when something is partly in view. Each posture P that is generated is recorded as an identifier in a file.

### 3.4 Image Rendering

In order to teach the system, we produce RGB pictures artificially. The first column of the fourth figure depicts a good illustration. We had to strike a balance among picture file size as well as data density. More data is available for estimating purposes with larger photos. They also include elements like dust, dirt, scratches, manufacturing residues, and other factors that are hard to reproduce in synthetic information. This may restrict a network's extension.

We maintained a standard picture size of 299299 pixels throughout the design process. With that level of detail and field of view,  $\varphi = \varphi_h = \varphi_v = 60^\circ$ , A lateral shift of 0.386" " cm per picture at far away of 100" " cm is theoretically conceivable:

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

Unity's 3D 6 is used to create the visuals. We load the whole labeled data file (P) and cycle through each possible camera posture (p). For more information on how we collect real-world photographs with our actual camera. That is carried out so that the final network can more accurately estimate depth in real-world pictures. Consistent data improvements are taken into account for the presentation. The light is uniformly dispersed. We account for specular reflection. Every picture has a translucent backdrop that will be covered throughout learning as a stopgap measure to improve the quality of the information. Each picture is stretched using the LanczosFilter as well as produced at 16x target frequency (four times each image dimension [width height]). Randomized Grid Super Sampling Anti Aliation [8] is a technique used for anti-aliasing that does not alter the original picture. At last, a picture is produced and saved on disk for every caption.

The icosaheder decomposition is carried out with 400 division per edges to deal with the rising information need for the constant data upgrades. As a result, n1.6106 pictures make up the last set of images. Since PNG is a loss-free compressing design, we only need 40-80 GB of total RAM for our applications.

Before instruction, the thing in the picture has lighting as well as reflections baked onto it permanently. As such, they are seen as a consistent improvement in statistics (Figure 4, columns A).

- Light's intensity as well as angle of incidence affect how things seem, with self-shadowing as well as reflected light playing a role.

To achieve this broad effect, the lighting conditions of each representation of the item are independently randomized. In our industrial setting, we may safely presume that illumination is constantly coming in from above. For this reason, we use a vector that is random with an even distribution for the illumination source, with the average position having a top-down, center look at the item.

- Reflections - Unity3D's re-flection sensors' values of intensity are dynamically shuffled to generate a variety of reflections. Our digitized substance database defines the materials and their fixed qualities (metallic and smoothness). In addition, an actual image is randomly chosen from the COCO collection [9] as well as oriented to form a cubic environmental mapping that is then pro-projected onto reflection probe. This is achieved utilizing environmental mapping [10], which generates a reflection independent of its backdrop (a new, arbitrary backdrop is produced during retraining).

#### 4. Implementation and Experiment

In this paragraph, we will discuss the system architecture, including the platform, applications, use cases, experiments, and conclusions.

##### 4.1 Platform

The system architecture of the developed AR application is depicted in Figure 4. The applications were developed using unity 3D Engine and Vuforia SDK. Initially the target images were uploaded in the Vuforia Target Management in Vuforia portal.

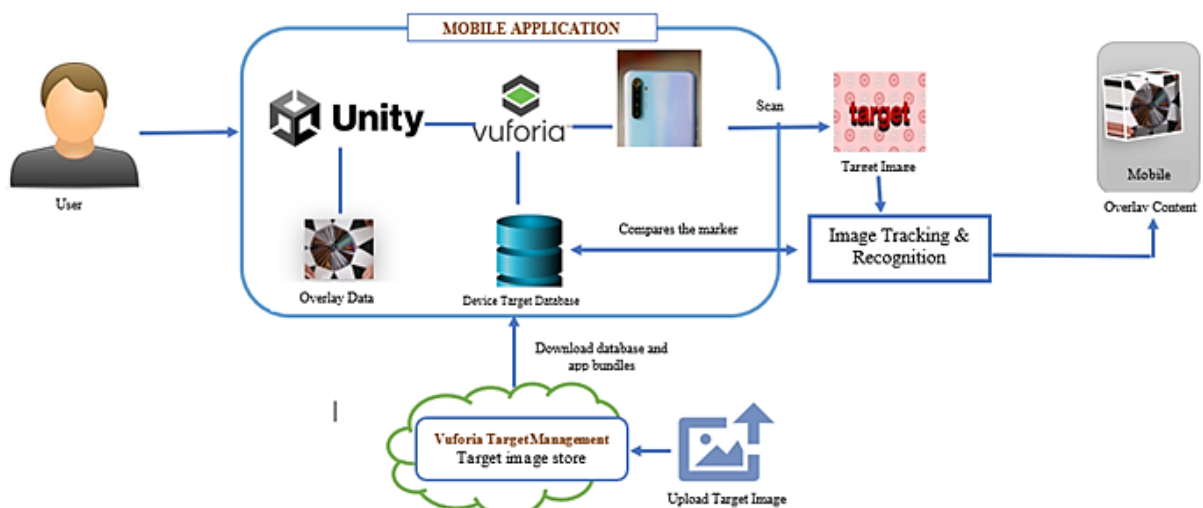


Fig. 4. Architecture diagram of AR applications

The user interaction display was designed using Unity Engine and the target database was imported. The overlay content stored in unity asset is assigned to the target images. Then the AR applications were converted into deployable apk using Android SDK.

**Table 1**  
 Software and hardware specification

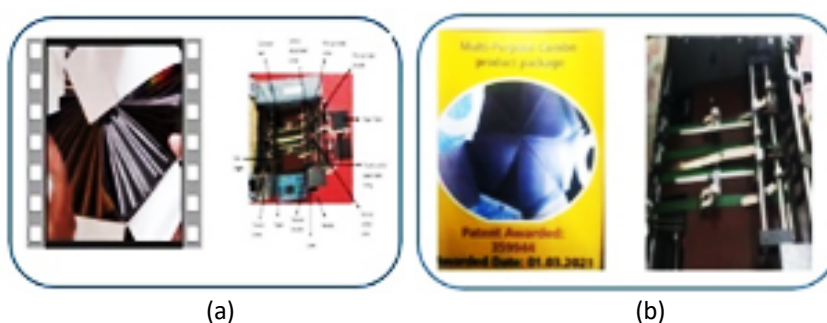
S. No	Software/hardware	Specification
1	Unity 3D engine	Unity 2018.4.36f1 (64-bit)
2	Vuforia SDK	Vuforia SDK Version 8.3.8
3	Visual studio	Version 2017
4	Android SDK	Version 4.1 'Jelly Bean'
5	Light luminous	LUX
6	Processor	Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz 2.50 GHz
7	Installed RAM	16.0 GB
8	Smart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

#### 4.2 Use Cases

There are two use cases used for developing the augmented reality applications. The use cases for the AR Apps:

- i. Combo box
- ii. Offset Colt Machine

There are two sets of target images used for developing the applications (offset printing machine and combo box) with two different overlay content (image and video) respectively. The overlay video of the combo box explains about its usage whereas the overlay image of the offset machine depicts different parts of the machine. Size of the overlay video is 40.7 MB and image is 123KB. The Target images of the use case are of different resolution, high, medium and low based on the image quality rating in Vuforia Development Portal. The light luminous of the environment was calculated using an application LUX, procured from play store. There are two types of target images used in testing the performance of the applications are digital form and printed form. The target images for the AR applications developed are shown in Figure 5(a) and Figure 5(b) depicts the overlay content for the target images respectively.

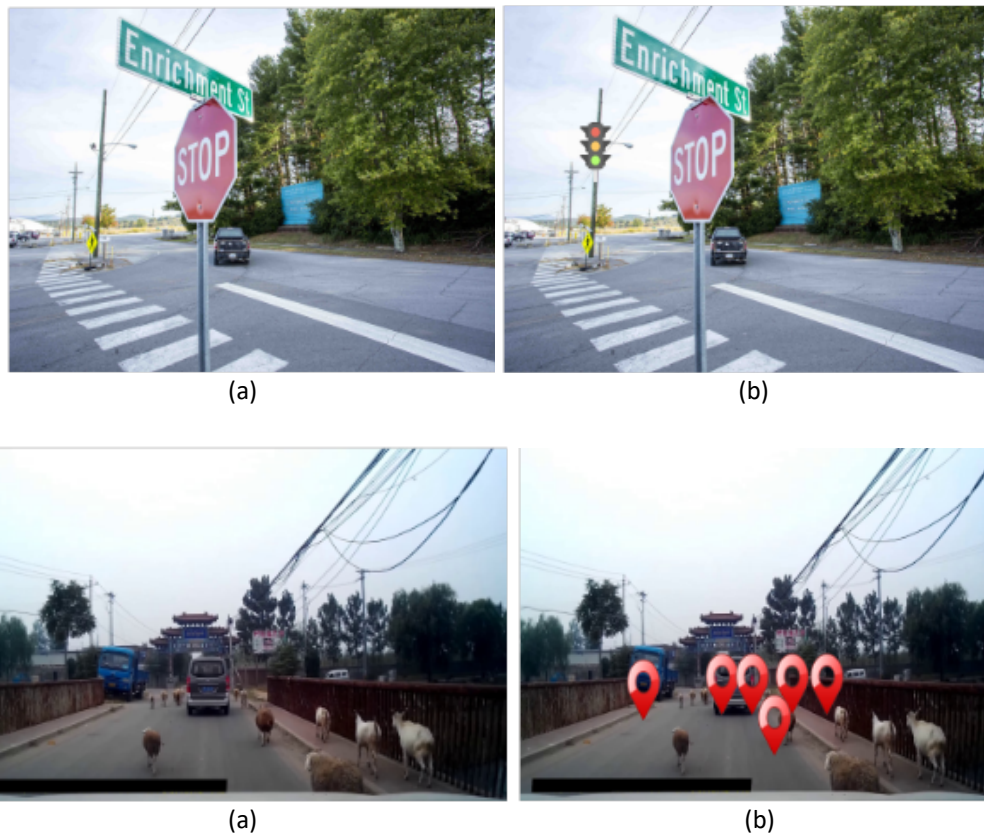


**Fig. 5.** (a) Target image (combo box and offset machine) at 104 LUX  
 (b) Overlay insight of the target (video and image)

Figure 6 shows the aforementioned instances demonstrate that our technology is able to recover sources of light which aren't apparent in the shot by learning how to map from picture appearances to scenario lighting from enormous volumes of actual image data. Our lighting predictions make it possible to accurately relight digital objects as well as merge them into pictures.

When the user (with a smart device) scans the target image (combo box and offset machine) using mobile phone the Vuforia camera of the application tracks the marker in the image, as shown in Figure 6(a). Compares with the target stored in the device target database, recognizes the marker and retrieves the overlay insight (video and image) respectively, as shown in Figure 6(b).

To test the efficacy of our method, we conducted user research in which subjects were prompted to select the more genuine of two photos featuring the same re-illuminated virtual item under either the ground-truth or estimated lighting scenarios. A total of 41.8% of respondents found our predicted illumination to be exactly the same as, or more genuine than, the ground truth result. This is a substantial increase in performance over the prior experiment, which achieved a maximum of 27.7%. More information about this project, along with variations suitable for use in environments outside.



**Fig. 6.** (a) Target image (combo box and offset machine) at 104 LUX (b) Overlay insight of the target (video and image)

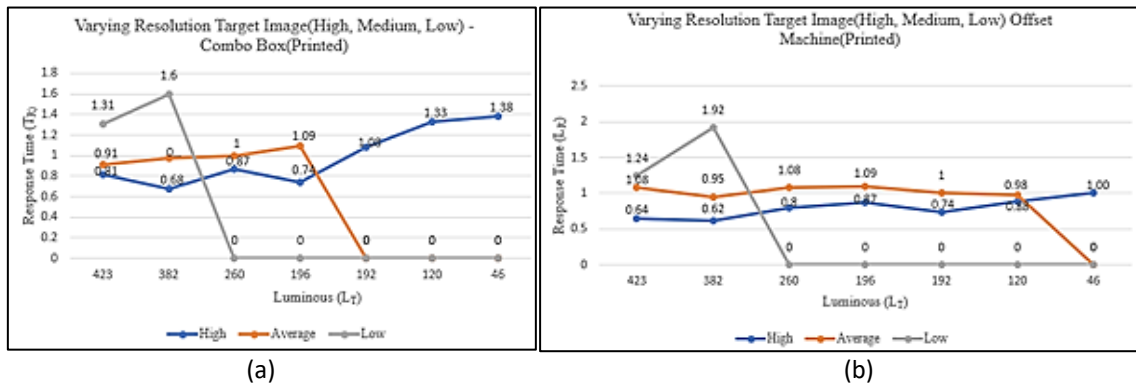
### 4.3 Experiment

The performance of the applications is measured in terms of the response time of the overlay content. The different overlay content displayed are video and image. The reliability is tested with different scanning light intensity, distance between the marker and the source of light and the type of target image (ie. Digital or Printed material) with different resolutions.

There are different tracks of light intensity used, (i) incandescent light (ii) fluorescent light and dark (low light source). When an obstruction is placed among the light supply as well as the object to be illuminated, the luminous flux decreases to 46 Lux from its maximum intensity of 423 LUX. A LUX light sensor program was used to evaluate the luminance level. The lens of the camera is 15cm away from the object being photographed. The two different forms of target images used were digital and printed material.

### 4.3.1 Digital target image

Response time of the application with digital target is depicted in Figure 7. Performance of the applications are tested using digital image as target in different scanning light intensities and the distance between the marker and the camera.

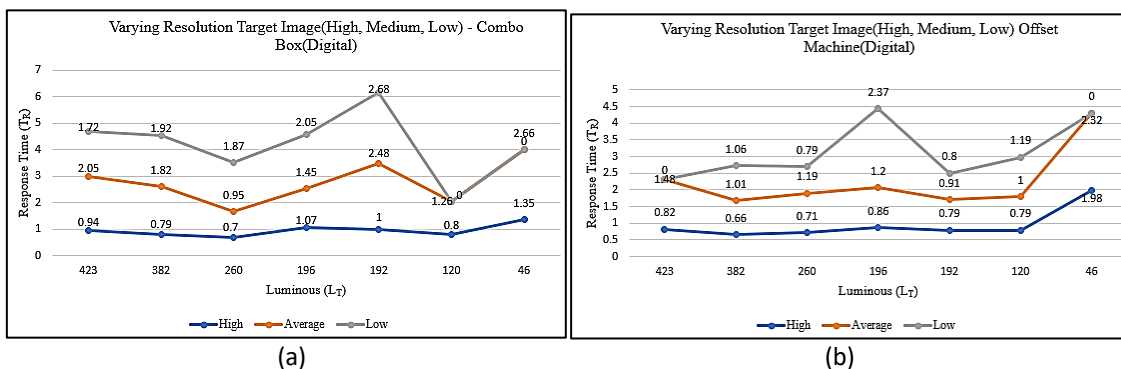


**Fig. 7.** Response time of the AR applications under varying resolution of printed target images, different scanning light intensity and distance (a) Combo box (b) Offset machine

When the target image is printed, with different light intensity, the response time of the overlay insight is measured. It is observed that, when the target image resolution is high, the response time is optimal with the varying light luminous. When the target image resolution is average, then the response time increases with change in light luminous. As the light luminous is decreasing, the response time of the application is higher. It is observed that when the light intensity is high, the response time of the overlay insight is optimal and when the light intensity varies. When the resolution of the target image is low, the response time of the overlay insight increases and no overlay is found at certain low intensity. The response time also depend on the color variant printed as the target. If there is little color deviation in printed target, the response time varies accordingly. The light luminous (L<sub>T</sub>) is proportional to the response time (T<sub>R</sub>) of the overlay insight of the application.

## 5. Results

With digital image as target, at 260 Lux and 46 Lux, the response time of the application was higher and no overlay is augmented at very low intensity. By increasing the brightness of the mobile there was variations in response time, depicted in Figure 8.



**Fig. 8.** Response time of the AR applications under varying resolution of digital target images, after increasing mobile brightness

The response time has certainly increased while the brightness of the mobile has increased.

Following are the few observations during the experiments.

- i. The performance of the application varies with the digital target images and printed target images. the performance of the app with digital marker is lesser than the printed markers due to the reflection of light on the target image.
- ii. Moreover, the colors in the markers play a vital role in image recognition. The recognition of gray scale markers is faster than the RGB markers.

## 6. Conclusions and Future Work

In this research, we introduced deep learning-based approaches to two difficult visual analysis issues: 6-degrees-of-freedom object tracking and brightness estimate. In both situations, state-of-the-art outcomes are obtained by training deep convolution artificial neural networks on massive datasets. As a result, we expect these kinds of technologies to pave the way for more lifelike apps using augmented reality capable of respond to varying lighting and dynamic environments. The target markers can be of three forms namely, real objects, printed markers and digital markers. The experiment was performed with two of these markers such as printed and digital markers. The above experiment concludes that the response time depends on light intensity. The response time of the application can also be obtained while increasing the brightness of the smart device (mobile phone) rather by increasing the light source. Finally, it is observed that the printed markers efficient than the digital markers due to the reflections. The experimentation with the real object as marker depends on source of light, intensity, distance, reflection of object, object texture, surface, etc.

Future work involves developing the remaining app with real object as target and obtain the performance of the application.

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## **AUGMENTED REALITY-DRIVEN TECHNICAL EDUCATION FOR SUSTAINABLE INDUSTRIAL PRACTICES AND ENVIRONMENTAL AWARENESS**

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**Abstract.** Augmented Reality (AR) enabled learning interventions on improving sustainable industrial practices and environmental awareness are useful in technical education. Within a total of 100 undergraduate engineering students, two groups were chosen (Group A: control using traditional learning methods using lectures, textbooks, and discussions; Group B: experimental using AR-based simulations). In this research, each group was tested pre- and post-test to provide data on what groups measured their increase in knowledge of sustainability concepts. Results indicated that Group B showed a higher mean post-test score for AR learning, which was statistically significant from Group A GEOG 6259. For instance, Group A's mean pretest score was 74.77 (SD = 7.62) while the mean post test score was 85.07 (SD = 6.26) and the amount of mean improvement was much greater at 10.30 points (SD = 9.47). Thus, these results point to the fact that AR interventions prove to be more effective in helping people understand and remember sustainability concepts. In addition, the analysis of individual pre-test and post-test scores in a scatter plot showed an expanded impact of Group B, that is more personalised and engaging learning through AR. The statistical summary indicated that Group B had better engagement and environmental awareness as indicated by the high increase in knowledge and application of sustainability practices. Lastly, AR driven education is better, more immersive, interactive, and effective than normal education which results in a better understanding of the implementation of sustainable Industrial practices, and increased environmental sensitivity. According to these findings, AR has the potential to be a revolutionary force for technical education within complex fields including sustainability when students learn through an interactive and hands-on approach.

*Keywords:* augmented reality (AR), technical education, sustainable industrial practices, environmental awareness, industrial simulation, eco-friendly practices, energy efficiency and waste reduction.

### **AIMS AND BACKGROUND**

The main objective of this study is to investigate how AR can supplement technical education with sustainable industrial practices and environmental awareness. Among others, as industries around the world are under more pressure to become more sustainable, educational tools to bridge the gap between theory and practice in sustainability are very critical. It is quite common for traditional educational

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methods to not provide students with the experiential learning required to provide a full understanding of industrial operations and the complex environmental impacts of these operations<sup>1</sup>.

This ability of the AR to superimpose digital content into real world provides an immersive and interactive platform for learners to experience industrial processes and environmental phenomena firsthand<sup>2</sup>. Through visualisation of industry systems in real time, the students can manipulate models, simulate the operation, and see the consequences of practice on the environment interact with each other<sup>3</sup>. Through these hands on approach, people tend to engage and understand more thus making them take informed decisions regarding the appropriate use of Sustainable practices<sup>4</sup>.

Integration of AR can greatly benefit technical education, particularly fields such as engineering, manufacturing and environmental science<sup>5</sup>. Learners can explore energy efficient production methods through through AR driven simulations, and how they are or are not impacted by waste management strategies, and the environmental impact of industrial processes via AR driven simulations<sup>6</sup>. AR can also be used to teach the difficult concepts such as the circular economy, resource management and the life of a product in a sustainable industrial ecosystem<sup>7</sup>.

In technical education, the use of AR not only increases the knowledge but also develops skills in critical thinking, problem solving and creativity<sup>8,9</sup>. AR can be instrumental in inspiring a workforce who are both environmentally aware and technically adept by preparing students for the obstacles facing sustainability and the global change it brings<sup>10-13</sup>. This paper discusses the potential roles of AR in inducing environmentally friendly industrial practices and heightening the environmental consciousness to support the gain of a more sustainable future in industrial operations<sup>14,15</sup>.

## EXPERIMENTAL

This experiment aims to assess the impact of Augmented Reality (AR) in reinforcing technical education by encouraging a deeper learning of sustainable industrial practice and an environmental awareness. This research compares AR-based learning with traditional education methods in order to determine whether AR can be better engaging in helping students understanding of complex concepts about sustainability in the industrial setting.

*Objective of the experiment.* The main focus of the experiment is to investigate how AR assists in understanding the practices of sustainable industrial processes and environmental impacts. Traditional education lacks the ability to supply immersive, overly interactive experiences that enhance theoretical concepts to real world applications. The objective of this study is to determine whether AR can bridge this gap by providing interactive, dynamic, simulations that enable students

to interact with the industrial environment, viewing and manipulating the effect of whether certain actions will have on the environment.

*Hypothesis.* There are two hypotheses behind the experiment. In the first hypothesis, AR-based learning methods will considerably improve students' understanding and retention of sustainable industrial practices than conventional teaching methods. Second, the idea that students using the AR-based simulations will show increased environmental awareness, are able to make informed, sustainably oriented decisions on industrial challenges.

*Participants.* 100 undergraduate students of engineering, environmental science and industrial design programs at a university in Tamil Nadu were the participants for the study. The students were randomly divided into two groups: (1) Group A – the control group, that were meant to be subjected to the traditional educational methods (lectures, textbooks, and case studies); and (2) the experimental Group B took place in AR-driven simulations which would include Working with the AR industrial simulations for sustainable industrial practices and environmental issues. At the beginning of the experiment, the baseline knowledge of all participants to the sustainability concepts was measured.

*Materials and tools.* An experiment requires AR simulation software, AR compatible devices (e.g. tablets, headsets), as evaluation tools for students in the learning outcomes in AR. Interactive industrial simulations that observe the environmental impact of industrial processes were included in the AR software. By the devices, students got to play with virtual models of factories, energy systems and waste management practices that would allow one to manipulate them hands on. The tools of evaluation included pre- and post-tests to measure the improvement of knowledge and surveys to understand students learning experience.

*Pre-test assessment.* Before the intervention, both groups first underwent a pre-test to ascertain their first knowledge level about sustainable practices. For this test one had to answer a multiple choice question and problem solving scenario type of questions to see their knowledge of industrial operations, environmental impacts and waste reduction strategies, resource management and energy efficiency. The measure of the initial knowledge levels at the beginning of the experiment was the pre-test, which was taken by both groups and acted as a measure for both the groups to compare.

#### INTERVENTION/PROCEDURE

*Traditional learning (Group A).* Group A was engaged in the traditional learning methods such as lectures in sustainability, textbook reading and discussions in groups. These methods allowed students to get to know about the theoretical knowledge connected to the sustainable industrial practices, include energy conservation

techniques, waste handling strategies along with the impacts of industrial activity on the environment. Nevertheless, they would not have the capacity to fully leverage these methods in providing hands-on experiential learning opportunities<sup>16</sup>.

*AR-based learning (Group B).* On the other hand, students worked with AR-based simulations that involved working with virtual models of an industrial environment in Group B. In these simulations, students adjusted different facets of industrial operation (energy cost, waste removal, resource management) and see the environmental impacts of their action. Also, the AR simulations had visualisations of the broader environmental impact such as pollution levels and carbon footprints. It designs the AR intervention to be highly interactive, encouraging students to engage with various scenarios where they can make a decisions about whether sustain or not sustain industrial systems. In doing so, for instance, students might change energy use in a factory to observe how it impacts overall efficiency, emissions, or what kinds of waste management strategies could reduce pollution levels, and do so in a way for their own understanding and not for trying to prove the data right. These simulations immediately provided feedback to students that show how their actions produce immediate results so that the theory pays off in practice.

#### DATA COLLECTION AND EVALUATION

*Post-test assessment.* After both groups were exposed to the materials on sustainable industrial practices, post-test questions derived from the materials were administered in an attempt to determine how much the subjects have understood as well as their ability to apply the learnt concepts on real life situations. The post-test was of the similar nature to pre-test but the questions were slightly more intricate indicated by the use of problem solving tasks. This task entailed the students to assess a case based on an industrial operation for the possibility of making recommendations for the improvement of sustainability. The level of knowledge and the ability of making decision before and after the completion of the lessons were compared based on the result of the pre- and post-test.

*Surveys and questionnaires.* As an element of the feedback, the students participated in the surveys in order to describe their attitudes to the learning process. The surveys included the following special interest areas/ domains:

Promotion: How interactive were the students when using AR simulations and how did they compare the experiences of using AR compared to conventional approaches.

Regarding environmental awareness, it is useful to determine whether the use of AR-based learning helped the students improve their awareness of environmental issues and sustainability in the industrial context.

*Qualitative interviews.* The participants were twenty students: ten from each group to make a template of interviews with open-ended questions; designed to provide

qualitative information regarding the students' learning process. The interviews included questions aiming at determining the students' perception on AR-based learning, whether their understanding of sustainability changed after the learning process, and if the application of AR transformed their decision-making processes in the real industrial settings.

#### DATA ANALYSIS

*Quantitative analysis.* In order to test the hypothesis, tool used on quantitative data included the use of test and variance from the initial and final exam scores. Mean and measures of variability like standard deviation gave a general approximation on the performance of one the groups in the test while signed *t*-test was used to check if the difference in the score of one group before and after the test is significantly different<sup>17</sup>. The formula that is used in *t*-tests is as follows:

$$t = X_d / (s_d / n^{1.2}),$$

where  $X_d$  is the mean difference between pre- and post-test scores,  $s_d$  – the standard deviation of the differences, and  $n$  – the number of paired observations.

*Qualitative analysis.* For qualitative data, we used thematic code to extract common themes from students' interview responses. This gave an insight about how students find the AR learning experience, the engagement level in the AR learning experience, and how the AR learning experience helped the students to develop critical thinking about sustainable practices. It was also performed content analysis of the survey responses to identify trends in students' attitudes to AR based learning.

#### EXPECTED OUTCOMES

At knowledge and environmental awareness between students of A and B groups it was expected that those of B (AR-based learning) group would be improved more than A group. The results of this test were seen in their post-test scores, and Group B was likely to show a greater ability of applying sustainability concepts to practicing situations. Furthermore, survey and interview data were anticipated to show the role of AR driven simulations as being considered a more engaging and effective way to transmit the complexity of environmental concepts.

For the purposes of assessing the potential of AR as an educational tool for encouraging sustainable industrial practice and raising environmental awareness, this experimental design was based. AR has the capability to revolutionise students' ability to understand complex sustainability issues by providing an immersive and interactive learning experience through it. Based on the results from this study, the results could offer valuable insight into how AR can be inserted into technical education to cultivate a more ecologically aware and educated workforce<sup>18–20</sup>.

## RESULTS AND DISCUSSION

### PRE-TEST SCORES COMPARISON

The pre-test scores of both group A (controls group) and group B (experimental group) are shown in Table 1. Both groups have similar average pre-test score with Group A's average pre-test score of 61.12 and Group B's average pre-test score of 60.78. This slightly different mean score suggests that both groups were on the same range about the baseline knowledge in sustainable industrial practices and environmental awareness. Both groups have moderate standard deviation and Group A's is a little higher, 6.48, from Group B's 6.23. This means that Group A had a larger variation in their pretest scores which may imply that the group had a more various background than Group B. However, baseline understanding of the two groups was similar, therefore they were ideal between groups for comparison during the experiment.

**Table 1.** Pre-test scores comparison

Group	Mean pre-test score	Standard deviation	Min. score	Max. score
Group A	61.12	6.48	50	74
Group B	60.78	6.23	52	74

### POST-TEST SCORES COMPARISON

The results from the post-test after the learning interventions are shown in Table 2. Group A scores an average of 66.43 on post-test, which is not a big improvement from their pretest scores (61.12). On the other hand, Group B's average post-test score (74.12) is a more pronounced increase than what it has shown in its pre-test score (60.78). For Group A, there is an approximately 5 point improvement while in Group B, the mean improvement is approximately 13 points. The difference of this great extent between the two groups emphasises the possibility of using AR-based learning (used in Group B) as a better method than traditional education method to increase understanding and retention of sustainability industrial practice. The post-test scores in Group A (7.02) is a little lower than the post-test scores in group B (7.82), which means that the range of post-test scores in group B was a bit wider than group A. It could be because of the levels of involvement with the AR simulations that the students might have differed from each other, with some being more active with AR simulations as compared to others. Although the variation was higher, Group B still had a much better average post-test score.

**Table 2.** Post-test scores comparison

Group	Mean post-test score	Standard deviation	Min. score	Max. score
Group A	66.43	7.02	57	84
Group B	74.12	7.82	60	90

### IMPROVEMENT IN SCORES

Table 3 shows the improvement in pre- to post-scores for both the groups. Group A shows a mean improvement of 5.31 points, with a standard deviation of 4.74. While this is a good thing, the fact that the learning interventions which were employed to Group A (traditional methods) had only a very mild impact to better students grasp of the sustainable industrial practices is a drawback. It is not enough to imply a great change in knowledge or attitude. Group B however, has a much greater mean improvement of 13.34 points and more standard deviation of 6.89. This improvement is influenced by AR-based learning, through which students were provided an opportunity to actively participate in their learning through their interactions with industrial simulation which enabled more immersive and dynamic learning process. With the higher standard deviation in Group B, it implies that some students improved their way better than others as in some students engaging well or they can use the AR tool properly. Finally, these findings indicate that traditional methods do not yield significant knowledge and understanding improvements in sustainability concepts, whereas AR is beneficial as an effective modality for attempting to achieve such results.

**Table 3.** Improvement in scores

Group	Mean improvement	Standard deviation of improvement	Min. improvement	Max. improvement
Group A	5.31	4.74	0	14
Group B	13.34	6.89	2	18

### PRE-TEST AND POST-TEST SCORE COMPARISON

The actual score changes for each participant, for individual pre-test and post-test for both groups are given in Table 4. To that end, some of the members of Group A had small improvements while some had minimal change of their scores. This ranges of improvements in Group A indicate that traditional teaching method may have been effective only to some and there may be different levels of effectiveness when prior knowledge or engagement with the material is varied. Whereas Group B's participants produce dramatically more noticeable improvement in their post-test scores, many students in this group score much higher in the post-test measures than they did in the pre-test. For instance, the post-test score of a student who had

pre-test score of 61 in Group B was 75 and another even exceeded the scores of as high as 85 or 90. This shows that AR based simulations can make teaching and learning more personalised, meaning that the students can actually understand the content at their own pace and that is better gains. The greater knowledge retention and understanding in Group B also adds to the notion that learning with AR can lead to a more general improvement.

**Table 4.** Pre-test and post-test score comparison

Group	Pre-test score	Post-test score
Group A (1)	60	65
Group A (2)	58	62
Group A (3)	63	68
Group A (4)	59	61
Group B (1)	61	75
Group B (2)	55	80
Group B (3)	67	82
Group B (4)	62	85

#### STATISTICAL SUMMARY OF IMPROVEMENT FOR BOTH GROUPS

Table 5 presents the statistical analysis that measures group improvement results between Group A and Group B. The data reveal that Group A performed under Group B since their mean score improvement amounted to 5.31 points while Group B achieved 13.34. The remarkable difference between test score improvements between these groups verifies the findings seen in all previous tables where AR-based learning demonstrated superior effectiveness with Group B. The results show Group B achieved wider ranges of improvement due to its higher standard deviation (6.89) compared to Group A (4.74). Multiple factors including student interaction levels and technical understanding along with initial knowledge of sustainability topics affect the range of changes observed in their final scores. Table 5 reveals evidence which supports the notion that students learn sustainable industrial practices better when using AR because it provides an enhanced learning experience. AR-based learning provided Group B students with better performance results accompanied by a wider variance in scores because of the dynamic nature of this educational method. Statistical analysis shows that using AR technology demonstrates promise for educational improvement when teaching difficult technical subjects such as sustainability.

**Table 5.** Statistical summary of improvement for both groups

Group	Mean pre-test	Mean post-test	Mean improvement	Std pre-test	Std post-test	Std improvement
Group A	61.12	66.43	5.31	6.48	7.02	4.74
Group B	60.78	74.12	13.34	6.23	7.82	6.89

## CONCLUSIONS

Finally, findings from this experiment clearly corroborate the potential of integrating AR in technical education in the area of sustainable industrial practices. AR clearly has the potential to bridge the gap between theoretical knowledge and practical application and hence, the substantial improvement in Group B's performance proves evidence of this. AR makes, Environmental issues complex, provide students with interactive, hands on learning experiences in industrial settings to make informed decisions about these issues. It does not only represent the powerful effect of AR in enhancing learning outcomes, but also, to some extent, figuratively showcase the capability of AR to cultivate environmental consciousness as well as prepare students for the reality of sustainability in industrial context. There are rich wonderful possibilities given the positive results that the widespread use of AR in education should be further explored, as it can revolutionise how sustainability and other complex concepts are taught in technical fields.

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