JOURNAL OF ADVANCED ZOOLOGY
ISSN: 0253-7214

Volume 44 Issue S-2 Year 2023 Page 3193:3201

Lumbar Scoliosis Analysis Using Deep Learning Based Technique

Dr. Vijay P. Singh[1], Mamta Koban [2], Geeta Salunke[3]

[1]*Professor, Department of E & C Engineering, School of Engineering, SSSUTMS, Sehore, M.P.(India)*
[2]*Research Scholar, Department of E & C Engineering, School of Engineering, SSSUTMS, Sehore and Assistant Professor, E & TC Engineering, AISSMS IOIT, Pune, Maharastra.*
[3]*Assistant Professor, E & TC Engineering, AISSMSCOE, Pune, Maharastra.*
[1] vijaybhabha12@gmail.com
[2] mamta.wanjre@gmail.com
[3]geetasalunke@gmail.com

Article History

Received: 29 July 2023

Revised: 28 October 2023

Accepted: 06 November 2023

Abstract— Medical image interpretation automation saves physicians time and boosts diagnostic confidence. Most medical imaging diagnosis is done manually or semi-automatically. These methods vary when performed by several physicians. This thesis includes mid- sagittal lumbar spine magnetic resonance imaging (MRI) images with labeling and spinal metrics. Two pieces were marked. Professional radiologists created pixel-wise masks to detect vertebral bodies (VBs) in each picture, which a panel of spine surgeons subsequently examined. An enhanced method (VBSeg) compares the segmentation work of traditional and deep-learning architectural techniques. A novel computerized spinal misalignment evaluation method may help spine surgeons make objective decisions about critical surgeries. Angular deviation classifies spondylolisthesis 89% accurately, whereas the area inside the enclosed lumbar curve zone classifies LL adequacy/inadequacy 93%accurately.

Keywords—**Deep Learning, Spinal Deformities, spondylolisthesis, Angular deviation**

INTRODUCTION

One issue with the traditional diagnostic process in spine research is poor interpretation and intervention during patient monitoring who suffers spinal disorders.

This paper highlights a challenge in healthcare where patients with similar imaging studies may exhibit different symptoms and functional abilities. This is a common issue in personalized medicine, where tailoring treatments to individual patients is crucial for effective care. The traditional approach often relies heavily on manual interpretation and may struggle to leverage the full scope of collected patient data for accurate intervention planning. To have more precise interpretation and to offer better treatment, artificial intelligence inspired applications are becoming so popular. Alternative ways to express the idea that machine learning algorithms can make sense of seemingly stochastic datasets, which can be challenging for physicians to interpret.

Artificial Intelligence can be best fitted to serve every sections of spinal disorder related Treatment. It started from accurately prediction of sections of spinal abnormality area to post-operative patient monitoring. The alternative ways to express the idea that with the assistance of artificial intelligence and machine learning techniques, patient's medical data can be easily extracted, processed, and analyzed. These processes are mainly classified into three categories:

- **Predictive Analytics**: To analyze patient data in order to determine possible patient's outcomes such as health condition, chances of illness, etc. predictive analysis is used.

- **Diagnostic Analytics:** It is the form of analysis which examines the medical data to determine why patient's health outcomes happened.

- **Prescriptive Analytics:** This comprehensive analysis analyzes patient's data to improve quality of patient's management process.

By utilizing artificial intelligence and machine learning, the extraction, processing, and analysis of patient medical data can be carried out with ease. Within the healthcare sector, artificial intelligence serves as an inclusive term denoting the use of machine learning algorithms and software, or artificial intelligence, to mirror human cognition in the analysis, presentation, and understanding of sophisticated medical and health information.

Deep learning as a mainstream of machine learning uses trainable computational models that contain multiple processing components with adjustable parameters to learn a representation of data. Deep Learning methods are mainly based on Artificial Neural Networks (ANN), which were inspired by information processing in biological neural systems.

LITERATURE SURVEY

The research work published which are related to the use of Artificial Intelligence and Machine Learning Techniques in spinal surgery has been studied and are reviewed. Following papers are considered to acquire the knowledge and understand the latest research in spinal surgery.

Zamir Merali, et al. (2021) [1] "proposed a convolutional neural network is used for the detection of possible compression occurred in cervical spinal cord. Convolutional neural network is a type of artificial neural network used for image processing."

John T. Schwartz, et al.(2019) [3] This paper reviews the adaptation of novel machine learning and deep learning algorithms in spine research. Significant Research is carried out on Spinal medical data. Machine learning and deep learning algorithms work efficiently with the help of Computer Tomography (CT) scan and Magnetic Resonance Imaging (MRI).The main areas of spine research include automated visualization, Preoperative planning and Intra-operative Assistance, Diagnostic and Clinical prognostication.

Galbusera, F., et al. (2019) [4] "presented a brief description of the various techniques that are being developed nowadays, with a special focus on those used in spine research. Then, they describe the applications of AI and ML to problems related to the spine which have been published so far, including the localization of vertebrae and discs in radiological images, image segmentation, computer-aided diagnosis, prediction of clinical outcomes and complications, decision support systems, content-based image retrieval, biomechanics, and motion analysis. Finally, they briefly discuss major ethical issues related to the use of

AI in healthcare, namely, accountability, risk of biased decisions as well as data privacy and security, which are nowadays being debated in the scientific community and by regulatory agencies”.

Altini, N., et al. (2021) [2] “proposed a framework that addresses the tasks of vertebrae segmentation and identification by exploiting both deep learning and classical machine learning methodologies. The proposed solution comprises two phases: a binary fully automated segmentation of the whole spine, which exploits a 3D Convolutional Neural Network, and a semi-automated procedure that allows locating vertebrae centroids using traditional machine learning algorithms. Unlike other approaches, the proposed method comes with the added advantage of no requirement for single vertebrae-level annotationsto be trained. A dataset of 214 CT scans has been extracted from VerSe’20 challenge data, for training, validating, and testing the proposed approach. In addition, to evaluate the robustness of the segmentation and labeling algorithms, 12 CT scans from subjects affected by severe, moderate, and mild scoliosis have been collected from a local medical clinic. On the designated test set from Verse’20 data, the binary spine segmentation stageallowed us to obtain a binary Dice coefficient of 89.17%, whilst the vertebrae identification one reached an average multi-class Dice coefficient of 90.09%. In order toensure the reproducibility of the algorithms hereby developed, the code has been made publicly available”.

Chang, M., et al. (2020) [9] “introduced the overall field of machine learning and its rolein artificial intelligence, and defines basic terminology. In addition, common modalities for applying machine learning, including classification and regression decision trees, support vector machines, and artificial neural networks are examined in the context of examples gathered from the spine literature. Lastly, the ethical challenges associated withadapting machine learning for research related to patient care, as well as future perspectives on the potential use of machine learning in spine surgery, are discussed specifically”.

METHODOLOGY

To add quantitative features to the images in the initialmeasurement series and complete the composite dataset, manual ground truth labels, are constructed. A similar dataset is made available to the public for research collaboration. In the second measurement process, spinal measurements are performed on the automated segmented images that produced the best quantitative results—in this case, ResNet-UNet—in order to establish correlation with the measurements found on the ground truth labels.

Objective of Research Work

- Study, analyze and compare various existing machine learning algorithms
- Study, analyze and compare various postero- anterio (PA) and lateral radiographs using machine learning techniques: Two radiographs CT scan and MRIs will be use for the Research work. Techniques from supervised and unsupervised machine learning will be implemented for analyzing these radiographs. Evaluation of performance parameters and comparison of results of each technique will be presented
- Implementation of an efficient deep learning based framework for spine research using various machine learning libraries, models and computer programming language
- Evaluation of various parameters related to implemented technique
- To present a mathematical model for extraction of clinically relevant spinal measurements including angular and

distance-based measurements.

- To introduce automated approaches for the classification of spinal deformations linked to spondylolisthesis, as well as the evaluation of lumbar lordosis in hyper, hypo, and normal configurations.

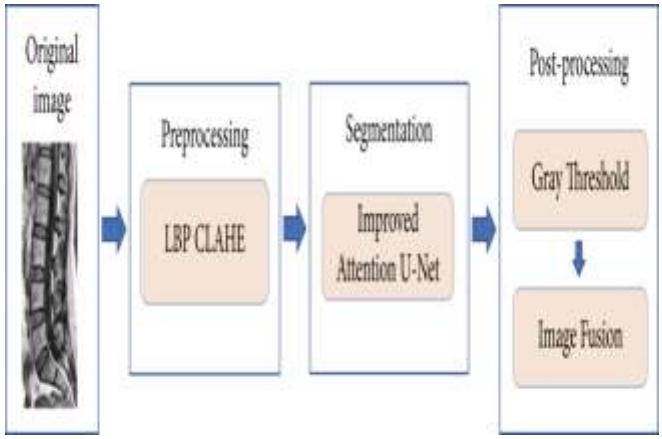


FIGURE 3.1: Thesis Framework

In Figure 3.2, the essential structure of the thesis is presented, delineating the sequence starting with input imaging, followed by VB segmentation that involves labeling and the identification of specific VB. The subsequent stage focuses on spinal measurements related to spinal geometry, and the final step involves automated classification of spinal disorders post the estimation of the spinal curve.

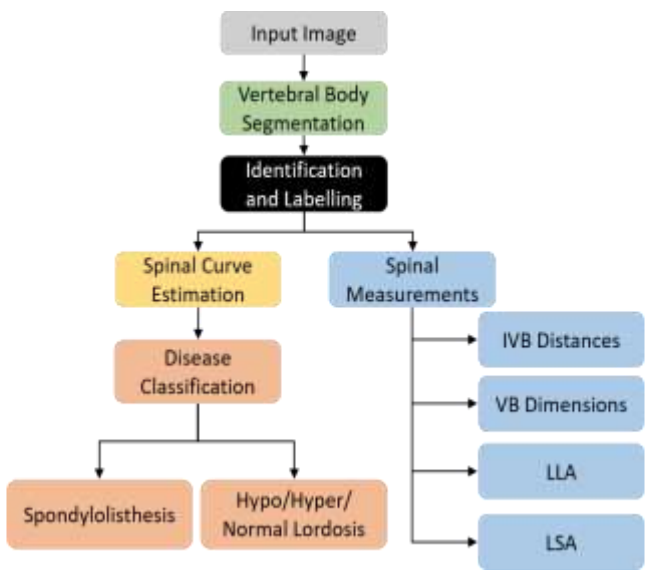


FIGURE 3.2: Thesis Framework

LUMBAR LORDOSIS ASSESSMENT

Prior to the actual intervention, the spinal surgeon manually conducts specific measurements to gain a deeper insight into the shape and structure of the vertebral column. Common methods involve the utilization of computer-assisted software and physically measuring dimensions on patients using flexible rulers, inclinometers, or spinal mice. Despite being the most crucial spine parameter, the quantitative evaluation of spinal curvature is limited due to potential variations introduced by manual or semi-automated handling by observers. In clinical settings, the ideal lordotic curve range is not fixed, and there are variations in LLA among male and female subjects, with significant differences observed in elderly subjects. As a standard practice, the lordotic curve should align with the pelvic incidence angle, with a tolerance of ±100. Typically, a standing X-ray radiograph is conducted for lordotic curve evaluation, followed by manual angular measurements, including the Cobb angle (Modified Cobb Method), which has become a standard for assessing the lordotic curve in the sagittal plane. As illustrated in Figure 3.3, θ denotes the angle of intersection between the perpendicular lines drawn from the superior end-plate of L1 and the superior end-plate of S1.

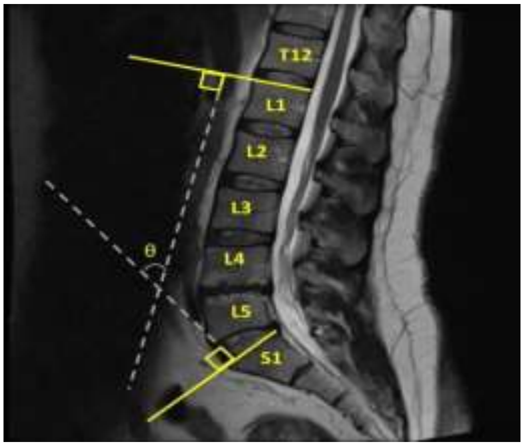


FIGURE 3.3: Cobb Angle θ Measurement Method.

As reported in research, a fundamental limitation of the Cobb method is its reliance on the end-plate structure for angle measurement. In response to this limitation, medical practitioners have introduced various alternative techniques. Some of them are mentioned below:

Ishihara Index:

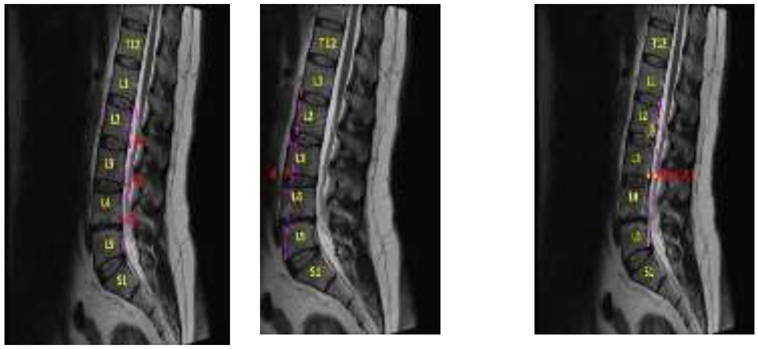
During the computation of the Ishihara index, a straight spinal line is formed by connecting the posterior-inferior corners of the superior vertebral body (VB) L1 and the inferior VB L5. Subsequently, the remaining posterior-inferior corners of the in-between VBs are connected perpendicularly to this spinal line. The Ishihara index is determined by the ratio of the sum of the lengths of the perpendicular lines to the length of the spinal line. In Figure 3.4a, the lumbar length from the inferior posterior L1 corner point to the inferior posterior L5.

Maximum Distance Method:

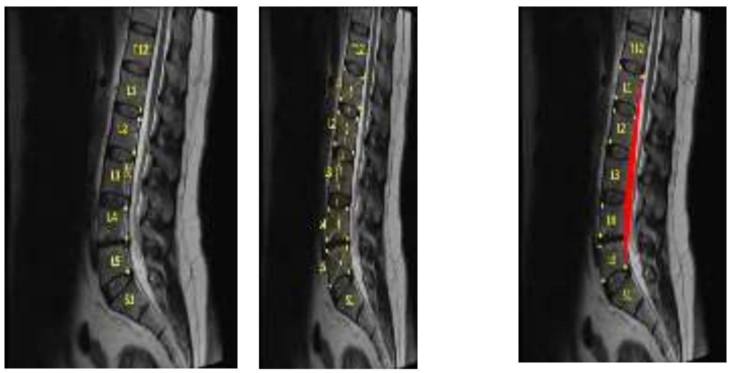
In this method, instead of joining the posterior corner points, anterior-inferior corners of superior VB and inferior VB are connected to form a straight spinal line representing thelumbar height. Maximum orthogonal distance from the spinal line and remaining in- between VBs is measured. The ratio of maximum distance and spinal length is measuredusing I = d, where, d is the maximum perpendicular distance between the anterior inferiorcorner points shown in red in Figure 3.4b to the lumbar height shown in magenta.

Tangential Radiologic Assessment of Lumbar Lordosis (TRALL):

In this method, posterior-inferior corners of superior VB and inferior VB are connected to form a straight spinal line represented by a magenta line in Figure 3.4c. Maximum orthogonal distance from the spinal line and remaining in-between VBs is measured as plotted in the red line in Figure 3.4c. Superior VB posterior-inferior point and inferior VB posterior-inferior points are directly connected to the corner point with maximum distance. The angle of intersection θ is measured.



(a)Ishihara Index (b) Max-Distance Method (c) TRALL Method



(d) HPTM (e) Centroid Method (f) AUC Method

FIGURE 3.4: Methods used for Assessment of Lordotic Curve.

Harrison Posterior Tangent Method (HPTM): The angle of intersection θ between the tangent lines made by connecting posterior- inferior and posterior-superior corner points of two superior VBs and posterior-inferior and posterior-superior corner points of two inferior VBs. As shown in Figure 3.4d, initially, a line is subtended from the posterior inferior corner points of the last two VBs followed by a line from the posterior inferior corner points of the first two VBs. The angle of intersection θ is the measure of the lordotic curve angle.

Centroid Method: The method proposed by Chen, in which the angle of intersection between the lines is connecting centroids of two superior VBs and the line connecting two inferior VBs. The opposing corner points of each VB are joined and the centroid is determined as the point of intersection of the opposing lines. The centroids are joined and the angle of intersection θ is measured as shown in Figure 3.4e.

Area under the Curve (AUC) Method: A curve is plotted connecting the posterior corners of lumbar VBs. The superior corner point is connected directly to the inferior VB corner point. The area enclosed in the region is measured. As shown in figure 3.4f, it is evident that this method requires software support to measure the area enclosed in the region of the spinal curve. Quite evidently, these alternate methods are more effort-demanding and calculation intensive once compared to modified Cobb angle measurement for assessment of lumbar lordosis. The alternate methods described above, involve multiple measurements, where the Chen centroid method was found to be the most calculation intensive and hence more reliable and the Yang method was calculated through software assistance and is not measured using manual methods. The reliability and reproducibility of these alternate methods were found to be superior to the modified Cobb method.

For the purpose of this research thesis, from the clinicians' perspective, a modified Cobb angle for lumbar assessment is considered for comparison purposes with the proposed method.

APPLICATION OF FINE-TUNING:

The most common and popular scheme of training the model being widely used is fine tuning. In this research fine tuning is performed various encoder decoder configurations by combining networks including ResNet-PSP_Net, MobileNets-UNet, VGG-UNet, ResNet-UNet, ResNet-SegNet and others. The process of fine tuning may be divided into four steps.

Picking a pre-trained model on a source dataset like ImageNet, let us call it the source model. Defining a model replicating the layers and parameters of course model however, last layer i.e., output layer is clipped.

It is defining a new output layer with desired number of classes as per the custom dataset and randomly initializing the parameters of the output layer. It also was appending of layer with the defined model Perform training of defined model on the custom dataset from scratch. Updating the parameters of last layers while fine tuning the rest of layers parameters.

The total number of epochs for training using fine-tuning, are 50 with the batch size of 2images. It was found that training time is the least for MobileNets-SegNet i.e., an average of 42.2 seconds per epoch, whereas the most for VGG-UNet i.e., an average of 465 seconds per epoch. The best performance for VB extraction is achieved by ResNet-UNet.

RESULTS

The corresponding findings have been grouped and organized in the same order according to each experiment so that the presentation would be clearer.

SEGMENTATION OF VBS: The comprehensive quantitative analysis is provided in table 4.1. The sub-captions are also included underneath each rowthat illustrates the different types of pictures that are shown in the graphic. In this section,we offer a chosen graphical comparison of the results achieved by the VBSeg algorithm with the segmentation results acquired by a variety of deep learning networks. Each row in the table shows the outcomes of applying a single technique to a variety of samples, while each column in the table represents the outcomes of applying numerous models andmethods to a single sample. A instance of failure is also provided in the second column from the left, where it can be observed that VBSeg completely misses the VBs. On the other hand, the results of deep learning approaches have been encouraging. It can also beseen that ResNet-UNet performs more effectively than the results obtained by other deep learning networks, such as the VBSeg algorithm that was initially proposed, despite the fact that VB-Seg is a specialized algorithm that has been thoroughly worked out to carry out VB segmentation tasks.

Table 4.2. Quantitative Comparison

	MPA	MPP	IoU	DSC
VBSeg (Pre-Validation)	96.34	57.46	0.49	0.67
VBSeg (Post-Validation)†	97.99	66.57	0.63	0.79
UNet	98.36	90.67	0.74	0.87
PSPNet	98.33	88.95	0.73	0.80
VGG-UNet	99.02	87.29	0.82	0.93
VGG-PSPNet	97.85	91.85	0.69	0.69
VGG-SegNet*	98.85	95.41	0.81	0.95
ResNet-UNet*	**99.12**	**98.31**	**0.86**	**0.97**
ResNet-PSPNet	98.08	95.66	0.72	0.76
ResNet-SegNet	98.59	98.06	0.78	0.93
MobileNets-UNet↓	97.50	81.33	0.67	0.63
MobileNets-SegNet*	98.63	88.71	0.75	0.87

SPONDYLOLISTHESIS: In the radiologist report mentioned that out of a total of 514 patients, 29 patients were diagnosed the spondylolisthesis. This diagnosis was based on the findings of the examination. Following the improvised angular deviation criterion, the suggested automated illness classification system obtained an accuracy of 89%. A few selected results where the classification model correctly identifies and labels the spinal dislocation disorder illustrated by 'Dislocation at L3'. This can be seen because the sub-images are displayed in the same location as the main image. In addition, the suggested method 3 accurately classified the usual situations that were labelled as "No- Dislocation,"

CONCLUSION

This paper introduces a consolidated dataset comprising highly detailed annotations of mid-sagittal views of lumbar spine MR images, correlated with spinal measurements. The primary aim of the autonomous lumbar spine toolkit proposed herein is not to replace the efforts of medical professionals but rather to offer assurance and reliability to the manual diagnoses conducted by clinicians. Utilizing the provided toolkit enables physicians to access reliable quantitative indicators, enhancing the precision of the selected or shortlisted surgical intervention techniques.

.*References*

[1] Zamir A. Merali, Errol Colak, Jefferson R. Wilson, "*Application of Machine Learning to Imaging of spinal Disorders: Current Status and Future Directions*", Global Spine Journal, Volume 11, Issue 1, 23 April 2021

[2] G.Michael Mallow, Zakariah k .Siyaji, Fabio Galbusera, "*Intelligence based spine care model: New Era of Research and clinical Decision Making*", Global Spine Journal, Volume 11, issue 2, 28 November 2020

[3] John T. Schwartz, Michael Gao, Eric A. Geng, Kush S. Mody, Christopher M. Mikhail, Samuel K. Cho, "*Applications of Machine Learning Using Electronic Medical Records in Spine Surgery*", Neurospine, Korean Spinal Neurosurgery Society, 643-653, 2019

[4] Fabio Galbusera, Gloria Casaroli, Tito Bassani, "*Artificial intelligence and Machine Learning in spine research*", JOR Spine, Wiley Publications, Orthopaedic Research Society, January 2019

[5] N. Altini, G. De Giosa, N. Fragasso, C. Coscia, E. Sibilano, B. Prencipe, S.M. Hussain, A. Brunetti, D. Buongiorn, A. Guerriero, et al., "*Segmentation and Identification of Vertebrae in CT Scans Using CNN, k-Means Clustering and k-NN*", Informatics, 2021

[6] M. Chang, J. A. Canseco, K. J. Nicholson, N. Patel, and A. R. Vaccaro, "The Role of Machine Learning in Spine Surgery: The Future Is Now," Front. Surg., vol. 7, no. August, pp. 1–15, 2020,

[7] Mamta S. Koban, Vijay P. Singh, & Rajesh Bodade, *"Investigation on Efficient Deep Learning Framework for Spinal Deformities: A Review Approach"* Journal of Pharmaceutical Negative Results, Oct. 2022, pp. 153–164.

[8] Mamta S. Koban, Vijay P. Singh, Rajesh Bodade, *"INVESTIGATION OF EFFICIENT DEEP LEARNING FRAMEWORK FOR TREATMENT OF SPINALDEFORMITIES"*, Journal of Pharmaceutical Negative Results, Dec.2022, pp. 3314–3324.

[9] Mamta S. Koban, A.A.Ansari, Rajesh Bodade, "*Localization and Prediction of Spinal Vertebrae Fracture in Human Body Using Deep Learning Approach: Review Paper",* 7th International Conference on "Shaastrarth-2022" on "Computational Optimization, Modeling and Simulation: Recent Trends and Challenges" on 25th – 26th March 2022, organized by Rungta College of Engineering and Technology, Bhilai, Chhattisgarh.

[10] Geeta D. Salunke, Vijay P. Singh and Chaya R. Jadhav, "A Review Approach to Modeling, Analysis, and Design Framework for Wireless Sensor Network Health Monitoring Systems". (2022). Journal of Pharmaceutical Negative Results, 165-177.

[11] Geeta D. Salunke, Vijay P. Singh and Chaya R. Jadhav, "DEVELOPMENT OF A CONTINUOUS MONITORING SYSTEM FOR HUMAN BODY TEMPERATURE AND HEART RATE SOUND. (2022). Journal of Pharmaceutical Negative Results, 3303-3313.

[12] Kashid, M. M., Karande, K. J., & Mulani, A. O. (2022, November). IoT-Based Environmental Parameter Monitoring Using Machine Learning Approach. In Proceedings of the International Conference on Cognitive and Intelligent Computing: ICCIC 2021, Volume 1 (pp. 43-51). Singapore: Springer Nature, Singapore.

[13] Dr. P. B. Mane and A. O. Mulani, "High throughput and area efficient FPGA implementation of AES algorithm", International Journal of Engineering and Advaned Technology, Vol. 8, Issue 4, April 2019

[14] A. O. Mulani and Dr. P. B. Mane, "Secure and area Efficient Implementation of Digital Image Watermarking on Reconfigurable Platform", International Journal of Innovative Technology and Exploring Engineering, Vol. 8, Issue 2,Dec. 2018 .

[15] P. B. Mane and A. O. Mulani, "High Speed Area Efficient FPGA Implementation of AES Algorithm", International Journal of Reconfigurable and Embedded Systems, Vol. 7, No. 3, pp. 157- 165, November 2018.