SETSCI conference proceedings
SETSCI Conference Proceedings
6 (1), 64-69, 2023

Cognitive Models and Artificial Intelligence Conference
26-28 October 2023, Ankara, Türkiye

https://doi.org/10.36287/setsci.6.1.025

BMYZ 2023

Assessment of Undergraduate Student Graduation Projects Focusing on Deep Learning in Biomedical Sciences

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Abstract – Biomedical Sciences are the technological disciplines that aim to explore methods to obtain, produce, reveal or produce information related to understand, model, monitor, diagnose, combat problems in human and/or animal bodies. Machine learning in biomedical technology is relatively new field of scientific research area and engineering technology application field, its growing rate is so fast that it is put into lower education levels than graduate level. In this work, educational contributions of senior year electrical and electronics engineering student projects will be discussed. After supervising four undergraduate student graduation projects, done by total of six students, it is concluded that the undergraduate electrical and electronics engineering average student is ready to apply deep learning techniques to biomedical sciences with restricted budget conditions, internet resources, available computational infrastructure and credit-hour load from the other courses leading graduation. Moreover, a student is already aware of and is ready to fully consider his professional work obligations health, safety, manufacturability, sustainability, economy direct or indirect effects to society, ethics, and environment..

Keywords – Biomeical Engineering, Deep Learning, Artificial Intelligence, ECG, ACS, Biology

I. Introduction

The concepts that come into our lives with artificial intelligence are machine learning and deep learning. While machine learning can be defined as a subgroup of artificial intelligence, deep learning is also a subgroup of machine learning.

Deep Learning in artificial intelligence is an emerging working area to aid classification and decision making to human efforts by means of computer hardware and software. It can help clinicians diagnose disease, identify cancer sites, identify drug effects for each patient, understand the relationship between genotypes and phenotypes, explore new phenotypes, and predict infectious disease outbreaks with high accuracy.

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain from large amounts of data. Deep learning drives many artificial intelligence (AI) applications and services that improve automation, performing analytical and physical tasks without human intervention.

Biomedical Sciences are the technological disciplines that aim to explore methods to obtain, produce, reveal or produce information related to understand, model, monitor, diagnose, combat problems in human and/or animal bodies. The researchers are working for living systems from the cell scale to human beings, to explore and analyse its systematic (normal) behaviours, any problematic (pathological) case diagnosis as well as designing and substituting parts of the body by using therapeutic or prosthetic devices.

Although the idea of artificial intelligence emerged at the end of the 1950s, it has gained a lot of popularity in recent years and its usage areas have become quite widespread. After utilisation in automated industrial application, the artificial intelligence is now in many fields of biomedical science both to aid human experts to lessen cumbersome routine biomedical activities, as well as reach out a few critical conditions to act like an expert, such as remote medical diagnosis and therapy systems in not so comfortable or even hazardous environments for the experienced medical expert. All these systems imitate human brain in computer environment, by means of computational models of human brain nerve cells, i.e. neurons. Interconnection of these neurons in computational domain is representation of neural networks in human nervous system by means of computational representation pieces in software application codes.

Neural Networks (NN) use the architecture of human neurons which have multiple inputs, a processing unit, and single/multiple outputs. There are weights associated with each connection of neurons. By adjusting these weights, a neural network arrives at an equation which is used for predicting outputs on new unseen data. This process is done by backpropagation and updating of the weights.

Even though, machine learning in biomedical technology is relatively new field of scientific research area and engineering technology application field, its growing rate is so fast that it is put into lower education levels than graduate level. In this work, educational contributions of senior year electrical and electronics engineering student projects will be discussed.

II. Materials and Method

The higher educational institute is internationally accredited University having Faculty of Medicine, Faculty of Engineering, Faculty of Education, Faculty of Arts and others, such as literature, social sciences. The syudents participated in this study is senior level students attempting to get B.Sc. Degree in Electrical and Electronics Engineering. In the senior level of their four-year education, a two-term project course is offered and the registered student is expected to compile existing information (techniques, articles, patents if applicable etc) about the topic of the project, then analyse the information, select the appropriate ones for the project. Then comes the implementation stage in which the student (or student group) is supposed to design the solution, construct the first prototype (hardware, software or hybrid), test its performance with respect to project constraints announced and agreed in the beginning. According to this first test, preliminary results are obtained, documented in interim reports and weekly progress reports. Followingly, second and further prototypes are developed, tested in more rigorous constraints, documented in the end of the year by term report, poster, descriptive video clip in internet environment and besides the project is defended against other lecturers and students in a common gathering in project exhibition format.

This work samples four of these projects offered in the last year to give some experience in deep learning experience in biomedical classification. The projects are briefly described followingly, where detailed information can be found in their project term reports as cited.

A. *Project 1 : Application of Deep Learning Algorithms to Classify Electrocardiography (ECG) Signals obtained from Acute Coronary Syndrome (ACS) [1].*

This project aims to use deep learning algorithm to classify some heart signals obtained from electrocardiogram (ECG) device. In addition, it is aimed to detect patients with "Acute Coronary Syndrome (ACS)" by means of this algorithm. ECG is a very important method used to observe the electrical impulses produced by the heart and to detect heart diseases. In addition, the EKG is very practical and is life-saving in many situations.

Electrocardiogram (ECG) is a widely used reliable, non-invasive approach for cardiovascular disease diagnosis. With the rapid growth of ECG examinations and the insufficiency of cardiologists, accurate and automatic diagnosis of ECG signals has become a hot research topic. Deep learning methods have demonstrated promising results in predictive healthcare tasks.

It was developed a deep learning algorithm to classify in 12-lead Electrocardiography (ECG) Signals obtained from Acute Coronary Syndrome (ACS). Acute coronary syndrome is a term for a group of conditions that suddenly stop or severely reduce blood from flowing to the heart muscle. When blood cannot flow to the heart muscle, the heart muscle can become damaged. Heart attack and unstable angina are both acute coronary syndromes (ACS).Acute coronary Syndrome is divided into classes in itself. The aim in this project is to detect ACS from ECG signals and to identify the ACS class of the existing disease.

There are three different classes of ACS :

i) Unstable angina is a change in the pattern of angina symptoms (chest discomfort), including prolonged or worsening angina and new onset of severe angina symptoms. People who have unstable angina do not have signs of heart attack on their ECG or blood tests.

ii) Non-ST-segment elevation MI (NSTEMI) is a heart attack that identified by blood tests but that does not produce typical changes (ST-segment elevation) on an ECG.

iii) ST-segment elevation MI (STEMI) is a heart attack that doctors identified by blood tests and also produces typical changes on an ECG (ST-segment elevation).

The method involves compiling biomedical heart signal (ECG) data from reliable datasets in internet. The ECG signal is first preprocessed to remove noise and identify clean beats, then segmented to delineate the various waveforms comprising each beat. The ST segments are then isolated and a mathematical transformation is applied to extract the coefficients describing the morphology of the segment, which are then applied as input to the model.

In this project, computer vision will be one of our most basic applications, as ACS classification will be made by using ECG signal images. The most appropriate tool for this project was found to be OpenCV(Open Source Computer Vision) , which is an image processing library with its teaching/training sites as well as many useful codes to construt the desired deep learning architecture.

There are more than 2500 algorithms for image processing and machine learning within the OpenCV library. With these algorithms, operations such as face recognition, distinguishing objects, detecting human movements, object classification, license plate recognition, processing on three-dimensional images, image comparison, optical character identification OCR (Optical Character Recognition) can be easily performed.

The data set was retrieved from internet resources. It is PTB-XL ECG dataset, which is a large dataset of 21837 clinical 12-lead ECGs from 18885 patients of 10 second length. The raw waveform data was annotated by up to two cardiologists, who assigned potentially multiple ECG statements to each record. The in total 71 different ECG statements conform to the SCP-ECG standard and cover diagnostic, form, and rhythm statements.

To ensure comparability of machine learning algorithms trained on the dataset, it was added to provide recommended splits into training and test sets. In combination with the extensive annotation, this turns the dataset into a rich resource for the training and the evaluation of automatic ECG interpretation algorithms. The dataset is complemented by extensive metadata on demographics, infarction characteristics, likelihoods for diagnostic ECG statements as well as annotated signal properties.

The statistics of the data in the dataset are given as follows: The patient gender information is, %52 Male, %48 Female; age range is 0-95 (Median=62).

The technical specification of the computer hardware used in the project is as follows : Dell Inspiron 15 7000 Gaming(2.8 GHz Intel i7 processor, 16GB RAM, GTX 1050 Ti 12GB Graphics card) and ASUS(Intel Core i5 processor,8GB RAM, NVIDIA GeForce GT 620 graphics card).

The most appropriate algortihm for this classifier was decided to be the Convolutional Neural Network (CNN) algorithm, which is one of the deep learning techniques.

CNN model started with the input layer. There are 8 layers after which the convolution process is performed. Afterwards, the average pooling was performed, taking the average value of the outputs. With the dropout layer, the number of outputs is reduced and a triple classification has been made by using the dense layer, which provides the transition of neurons or nodes between the layers.

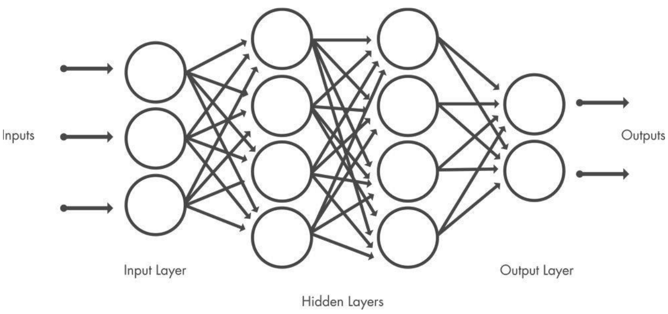

Fig. 1 Convolutional Neural Network (CNN) general

B. Project 2 : Processing and Classification of Microscope Images [2]

This project is related to cell scale, and involves microscopic imaging processing techniques. In the first phase, literature and dataset research was accomplished through available internet resources. The project time plan was constructed and steps to be taken were discussed.

According to data uniformity, blood cell datasets have been chosen. This data set was considered, data were investigated, pand classified by using CNN (Convolutional Neural Network) (Fig. 1).

The dataset contains 12,500 augmented images of blood cells (JPEG) with accompanying cell type labels (CSV). There are approximately 3,000 images for each of 4 different cell types grouped into 4 different folders (according to cell type). The cell types are Eosinophil, Lymphocyte, Monocyte, and Neutrophil. This dataset is accompanied by an additional dataset containing the original 410 images (pre-augmentation) as well as two additional subtype labels (WBC vs WBC) and also bounding boxes for each cell in each of these 410 images (JPEG + XML metadata). More specifically, the folder 'dataset-master' contains 410 images of blood cells with subtype labels and bounding boxes (JPEG + XML), while the folder 'dataset2-master' contains 2,500 augmented images as well as 4 additional subtype labels (JPEG + CSV). There are approximately 3,000 augmented images for each class of the 4 classes as compared to 88, 33, 21, and 207 images of each in folder 'dataset-master'.

'Blood Cell Images' dataset from 'Kaggle.com'. This dataset contains 12,500 augmented images of blood cells (JPEG) with accompanying cell type labels (CSV). There are approximately 3000 images for each of 4 different cell types grouped into 4 different folders (according to cell type). The cell types are Eosinophil, Lymphocyte, Monocyte, and Neutrophil. This dataset is accompanied by an additional dataset containing the original 410 images (pre-augmentation) as well as two additional subtype labels (WBC vs WBC) and also bounding boxes for each cell in each of these 410 images (JPEG + XML metadata). More specifically, the folder 'dataset-master' contains 410 images of blood cells with subtype labels and bounding boxes (JPEG + XML), while the folder 'dataset2-master' contains 2,500 augmented images as well as 4 additional subtype labels (JPEG + CSV). There are approximately 3,000 augmented images for each class of the 4 classes as compared to 88, 33, 21, and 207 images of each in folder 'dataset-master'.

The accuracy value for this model was calculated as approximately 0.783. This indicates that approximately 78.3% of all samples were correctly classified. The model accurately predicts most of the data.

In the second stage of the project, experimental works have been done to test the method in actual cell images obtained from inexpensive microscope. This microscope was a non-professional one, that a limited budget student can afford.

Various vegetable surfaces (watermelon, peach, hazelnut, tomato, etc.), blood, hair strands, flour items were imaged. These are the samples that can be found in every home and every student can access.

Following this experimental phase, a small classification group was created using onion varieties. The onion cells were chosen because their availability and repeatibility were the most compared to other samples. Normal onions, green onions and red onions were also included in the selected group of images to in order to inclrease onion cell image variations.

The cell samples have been examined and photographed different magnifications of at x100, x400 and x1200 zoom factors. The images have been classified these various onion images photographed with CNN, a deep learning method.

Recall shows how many of the real samples belonging to a given class are accurately predicted. In particular, the "NEUTROPHIL" class has a high recall value (0.88), indicating the model's ability to accurately predict this class. There are similarly high recall values for other classes.

In particular, a high precision value (0.96) was obtained for the class "EOSINOPHIL", indicating that the predictions of the model for this class have high accuracy if it really belongs to this class. There are reasonable precision values for other classes as well.

F1-score is a balanced measure of performance, combining precision and sensitivity. This shows the balance between precision and recall. Generally, the F1-score is a useful metric if the data is unstable. Separate F1-score values are calculated for each class and these values range from 0 to 1.

C. Project 3 : Implementation of medical decision support software library for classifying heart bioelectric signals [3]

Electrocardiogram (ECG) feature extraction is a process in signal processing and data analysis where relevant information is extracted from the ECG signal for further analysis or diagnosis. ECG is a graphical representation of the electrical activity of the heart over time, and it contains valuable information about the heart's rhythm and function. Feature extraction helps in quantifying and characterising specific aspects of the ECG waveform, which can be used for various medical applications, such as arrhythmia detection, heart disease diagnosis, and heart rate variability analysis.

The Adaptive Noise Cancellation (ANC) filter consists of the filter and adaptive algorithm, which updates the filter coefficients according to the reference signal. This method is based on the principle of the interference simulation as the reference input signal, which has to be associated with this interference. The estimated noise is subtracted from the raw measured signal to obtain the filtered one. The method can be used for the purpose of eliminating the PLI, baseline wander or motion artifacts.

Wavelet Transform (WT) is one of the most powerful time-frequency analysis means, which distributes continuous time signals into different scale components.

After the signal reconstruction using the wavelet decomposition structure, the signal that was non-stationary and non-periodic can become a smooth signal . The WT-based approaches are widely used due to their low complexity and high performance. They allow signal denoising with its lossless compression, R peaks detection or automated diagnosis determination of some diseases.

Here are the steps involved in ECG feature extraction and some commonly extracted features:

Data Acquisition: ECG data is typically acquired using electrodes attached to the skin, which record the electrical signals generated by the heart. This data is usually represented as a time-series waveform.

Preprocessing: Before feature extraction, it’s essential to preprocess the ECG signal to remove noise and artifacts. Common preprocessing steps include baseline correction, filtering (e.g., bandpass or notch filtering), and artifact removal.

R-Peak Detection: The R-peaks correspond to the highest points in the ECG waveform, representing ventricular depolarization (contraction). Locating R-peaks is a crucial step in ECG feature extraction, as many features are calculated based on the R-R intervals.

Segmentation: The ECG signal is divided into smaller segments, typically around the R-peaks. Segmentation helps in analyzing specific sections of the ECG waveform, such as the P-wave, QRS complex and T wave.

Feature Extraction: Various features can be extracted from the segmented ECG signal. Here are some common features:

– Heart Rate: The heart rate can be calculated by measuring the time between successive R-peaks (RR intervals).

– RR Intervals: These are the time intervals between consecutive R-peaks and are used for heart rate variability analysis.

– Amplitude and Duration of Waves: Characteristics of the P-wave, QRS complex, and T-wave, such as amplitude and duration, can be important for diagnosing specific cardiac conditions.

– ST-Segment Analysis: Changes in the ST-segment can indicate myocardial ischemia or injury.

– Frequency Domain Features: Transforming the ECG signal into the frequency domain using techniques like the Fast Fourier Transform (FFT) can reveal frequency-related information.

– Nonlinear Features: Measures of signal complexity, such as entropy or fractal dimensions, can provide insights into cardiac dynamics.

Classification or Analysis: Once the relevant features are extracted, they can be used for various purposes, such as detecting arrhythmias (abnormal heart rhythms), diagnosing heart diseases, or assessing heart rate variability for stress or autonomic nervous system analysis.

Visualization: Visualizing the extracted features and the original ECG signal can help healthcare professionals in making diagnostic decisions.

The method used in this work is adopting Matlab (TM) library and construct required architecture to classify data. Matlab provides a deep learning framework called Deep Learning Toolbox that supports a variety of pre-trained Convolutional Neural Networks (CNNs) for various tasks.Alexnet is a popular CNN arhitecture designed for image classification tasks. It consists of multiple convolutional and fully connected layers.

Input Layer : AlexNet takes an input image of size 227x227 pixels with three color channels (RGB). The input image is preprocessed, which includes mean subtraction and resizing to meet the network’s requirements.

Convolutional Layers (Conv Layers) : These layers are responsible for feature extraction. Each convolutional layer uses a set of learnable filters or kernels to perform convolution operations on the input image.

Rectified Linear Unit : ReLU activation functions are applied after each convolution to introduce non-linearity.

Max-Pooling Layers (Pooling Layers): After each pair of convolutional layers, there is a max-pooling. Max-pooling reduces the spatial dimensions of the feature maps and helps in creating translation-invariant representation.

Local Response Normalization (LRN): LRN is applied after the first two convolutional layers. It enhances the contrast of the features and provides local competition among neurons

Fully Connected Layers (FC Layers): After the convolutional and pooling layers, there are three fully connected layers. These layers perform high-level feature extraction and classification. Dropout is applied to reduce overfitting during training.

Output Layer: The final fully connected layer has 1000 neurons, representing 1000 different classes in the ImageNet dataset. A softmax activation function is applied to compute class probabilities. The class with the highest probability is the predicted label for the input image.

Training: AlexNet is typically trained using the stochastic gradient descent (SGD) optimization algorithm. The network is trained on a large labeled dataset (e.g., ImageNet) to learn discriminative features and minimize the classification error.

The results of this project can be summarised in three basic conclusion :

If speed and simplicity are important, then KNN may be a good choice. If accuracy and robustness are important, then CNNs may be a better choice. If computational resources are limited, then PNNs may be a good option.

D. Project 4 : Development of Convolutional Neural Network for ECG Beat Classification to Detect and Categorize Myocardial Infarction [4]

This project is based on a convolutional neural network construction to classify ECG signals on the different categories of myocardium infarction (MI) disease (i.e. heart attack). In earlier phase, support vector machine (SVM), k-Nearest neighbour (KNN) and probabilistic neural network (PNN) structures were inspected and how successful they were with different classification tasks, up to 6 classes.

After a careful revision, it was decided to define 11 classes will are categorized by the CNN architecture (Fig 1). AI is created in MATLAB environment with neural network layers that makes up a convolutional neural network (CNN), with 11 outputs that matches the 11 beat types which needs to be classified. These classes are as follows; anterior (A), anterior lateral (AL), anterior septal (AS), inferior (I), inferior lateral (IL), inferior posterior (IP), inferior posterior lateral (IPL), lateral (L), posterior (P) and posterior lateral (PL), alongside with the healthy (H) class.

The heart signal data have been obtained from PhysioNet database and it was pre-processed to get rid of noise and remove baseline wander, alongside some other improvements with proper filters applied. Later on, these data are inspected with a MATLAB tool called ECGDeli, for R-peak detection. This detection is necessary to divide the raw, long ECG recordings into beats that could be given to a neural network for training and testing.

After the R-peak detection, the beats are segmented and kept on cells with their corresponding class types. Following this, 80% of the data is divided into training data, 10% as validation data and 10% as testing data. Neural network is created with 19 layers, 4 1D-convolution layers, 2 1D-maxpooling layers and the rest being mostly ReLU activation layers and dropout layers.

III. Results

All of the projects work have been presented to include classification asssessment results in Receivers Operating Curves (ROC) and various classification accuracy metrics such as accuracy, sensitivity, specificity, F1 score and similar. One sampla figure of confusion matrix is given for Project 4, Lead 5 in Fig. 2.

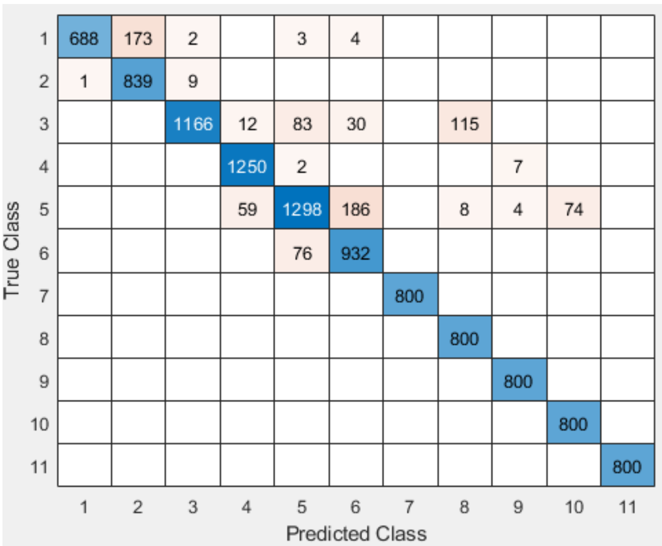

Fig. 2 Confusion matrix for Project 4 work for Lead 5 data

It was found that, the best average sensitivity was obtained in "iteration 2" as 97.81%, on lead 10 results. There are some weaknesses and strengths of the methods adopted:

Iteration 2 should be preferred when we want to inspect classes that didn't have much training data when we were training our neural network. Because by increasing their data number via Gaussian white noise addition and data recreation, we also decreased the chances of misclassification happening upon these classes from other classes that were overtrained, due to class imbalance and them having more training data. Yet fixing the class imbalance issue caused another problem, which was misclassification on other classes continuing to happen between each other and lowering the overall accuracy of the classifier. So, in overall sense, iteration 1 could be preferable. It has the highest accuracy rates on different leads, lead 10 being more preferable in MI-subclassification. It can also better distinguish healthy cases from other cases, compared to iteration 2.

IV. Discussion

Artificial intelligence (AI) aims to mimic human cognitive functions. Deep learning in AI can be applied to numerous types of biomedical data. These data can be structured (classical support vector machine and neural network), and unstructured (like natural language processing). for areas of early detection and diagnosis, treatment, as well as outcome prediction and prognosis evaluation. [5-6]

In the beginning of their engineering career, the undergraduate students will most probably face to analyse or design deep learning codes. Their undergraduate graduation projects are aimed to prepare the student to professional engineering environment.

Besides reaching out the golas of their technical aspects of their projects, it is also aimed to comply with applicable engineering standards exist to govern the rules of technical aspects and ethical aspects. Some standards can be itemised as;

ISO/TR 22100-5:2021: (Safety of Machinery-Relationship with ISO-Implications of artificial intelligence and machine learning. This document addresses how artificial intelligence and machine learning can impact the safety of machinery and machinery systems.)

ISO/IEC 2382-31:1997 (This document represents the detailed terminology about the artificial intelligence and machine learning.)

ISO/IEC 18039:2019 (Computer graphics, image processing and environmental data representation This document defines the scope and key concepts of mixed and augmented reality, the relevant terms and their definitions and a generalised system architecture based on image processing)

IEEE Standard 830 - Recommended Practice for Software Requirements Specifications: This standard provides guidelines for developing software requirements specifications. The project should satisfy this standard by ensuring that the software requirements specifications adhere to the guidelines set forth in IEEE Standard 830.

ISO 1348 5 - Medical devices -- Quality management systems -- Requirements for regulatory purposes: This international standard outlines the requirements for a quality management system for medical devices. Although none of the project yield a new biomedical device, it is still related to medical diagnostics and could benefit from following this standard to ensure that the system is safe, reliable, and effective. The project will satisfy this standard by adhering to the guidelines set forth in ISO 13485.

ANSI/ASQ Z1.4 - Sampling Procedures and Tables for Inspection by Attributes: This standard provides guidelines for sampling inspection procedures for attributes. In some projects, the sampling inspection procedures could be used to test the accuracy of the system's classifications by comparing them to manual classifications performed by experts. The project will satisfy this standard by following the guidelines set forth in ANSI/ASQ Z1.4.

ASTM E2817-18 - Standard Guide for Design and Development of Controlled Image Analysis Systems: This standard provides a guide for designing and developing image processing systems. This standard could be used as a guide to ensure that the project follows best practices for designing and developing the image processing and machine learning techniques used in the system. At least one project will satisfy this standard by following the guidelines set forth in ASTM E2817-18.

ISO/IEC 25010 - Systems and software engineering -- Systems and software Quality Requirements and Evaluation (SQuaRE) -- System and software quality models: This standard outlines the quality requirements for software products and systems. The standard provides guidelines for evaluating software quality characteristics, such as functionality, reliability, usability, and performance. This standard could be used to evaluate the quality of the system and ensure that it meets the necessary requirements.

ISO/IEC 14882:2011 (C++ Programming Language), that is general purpose programming language that was standardized, ratified and published by ISO in 2011. Because Python and MATLAB uses the same derived language with some additions and changes, our entire project will be based on this standard generally.

V. CONCLUSION

After supervising these four projects, done by total of six students, it is concluded that the undergraduate electrical and electronics engineering average student is ready to apply deep learning techniques to biomedical sciences with restricted budget conditions, internet resources, available computational infrastructure and credit-hour load from the other courses leading graduation.

Moreover, a student is already aware of and is ready to fully consider his professional work obligations health, safety, manufacturability, sustainability, economy direct or indirect effects to society, ethics, and environment.

The Sustainable Development Goals (SDGs), also known as the Global Goals, were adopted by all United Nations Member States in 2015 as a universal call to action to end poverty, protect the planet and ensure that all people enjoy peace and prosperity by 2030.

As an example, there are 17 SDGs and Project 1 agrees with two of them as mentioned below.

Goal 3: Good Health and Well-being

Goal 8: Decent work and economic growth

Goal 17: Partnerships on the Goals.

The other projects are also satisfy at least three of them from that requirement list.

ACKNOWLEDGMENT

This study was partially supported by Hacettepe University Scientific Project Coordination Office (BAP), Türkiye, Projects No: FYL-2018-17610, FYL-2018-17626, and FYL-2018-17469.

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