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A Review on Parkinson's Disease Detection Methods: Traditional Machine Learning Models vs. Deep Learning Models

Md. Toukir Ahmed, Md. Nazrul Islam Mondal, Debashis Gupta, and Mohammed Sowket Ali

ABSTRACT

Millions of people throughout the world suffer with Parkinson's disease (PD), severely reducing their quality of life. With the symptoms when we detect Parkinson disease automatically, it could provide insights to the disease's early stages of development, enhancing the patients' projected clinical results through correctly focused therapies. This potential has prompted numerous academics to explore ways for measuring and quantifying the existence of PD symptoms using commercially available sensors. In this paper, we offer an overview of some recent scientific articles on several machine learning techniques that assist physiologists in detecting PD early. In addition, a comparative study between traditional machine learning (TML) algorithms and deep learning (DL) architectures based on the scope of their appropriate usage for classifying PD effectively has been discussed. Based on the comparison on detecting the PD from previous works, this paper concludes that deep learning models are more efficacious than traditional machine learning algorithms.

Keywords: Deep learning, diagnosis, machine learning, Parkinson's disease, traditional machine learning.

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M. T. Ahmed *
Department of Computer Science & Engineering, Rajshahi University of Engineering & Technology, Bangladesh.
(e-mail: toukircse14@gmail.com)
M. N. I. Mondal
Department of Computer Science & Engineering, Rajshahi University of Engineering & Technology, Bangladesh.
(e-mail: nimbd109@gmail.com)
D. Gupta
Department of Computer Science & Engineering, Rajshahi University of Engineering & Technology, Bangladesh.
(e-mail: debashisguptaruet@gmail.com)
M. S. Ali
Department of Computer Science and Engineering, Bangladesh Army University of Science and Technology, Bangladesh.
(e-mail: sowket@gmail.com)

Corresponding Author

I. Introduction

The most common neurological disease is Parkinson's disease, which has a prevalence frequency of 1% for people above 60 years, affecting 1 to 2 people on average of 1000 [1]. From 1990 to 2016, 16 years duration, the number of infected population by PD have been approximately raised from 2.5 million to 6.1 million, which is almost double and mostly reflected in older adults [2]. A considerable loss of dopamine in the forebrain is assumed to be the etiology of Parkinson's disease, according to medical science. Cardinal motor signs such as bradykinesia, muscle rigidity, postural instability, tremor and non-motor manifestations (NMM) such as olfactory symptoms, sleep abnormalities, and bladder disturbances, are used to diagnose this infection [3], [4]. As detecting PD lately can seriously hamper the quality of life, especially for aged people, the diagnosis of this disease should be given priority which is currently addressed based on the motor symptom evaluation as per diagnostic standards. Two of the clinical scales named Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) and the Hoehn & Yahr (HY) [5] are basically utilized to check out the patients by giving a rating on the report of severity of disease. However, These scores are given on a case-by-case basis and can be influenced by a lack of consistency or fixed pattern since these scales are semi-quantitative. Several Machine learning approaches are being used now being widely used in medical science to assist physicians in detecting various diseases effectively at an early stage. These techniques typically allow a learning application on a computer and recognize the effective patterns from numerous data in a semi-automatic procedure. For example, machine learning models are applied to diagnose Parkinson's disease significantly from a plethora of data modalities based on movement, handwritten figures, cerebrospinal fluid, voice, neuroimaging, serum, optical coherence tomography, and cardiac scintigraphy. With the help of such models, relevant characteristics can be found which are not conventionally used in radiology and Parkinson's disease clinical diagnosis and therefore depend on these substitute estimations to perceive Parkinson disease in an atypical form or preclinical stages.

To date, numerous publications on detecting and segmenting PD using machine learning algorithms play a great role in aiding the physiologists and researchers in the medical sector to find an effective panacea. This review paper briefly discusses several machine learning methodologies recently proposed to detect PD successfully. Following this, we also show a comparative study between the deep learning

and the TML model to discuss how accuracy has been upgraded by using the later one.

II. Data Source and Performance Metric of the Investigations Included

In this study, we will face some databases to perform an article review that used machine learning (ML) architectures on different data to detect Parkinson's disease, to offer a detailed summary of the data sets and ML algorithms utilized in the detection of PD. The types of observed data from the literature review that this paper includes are shown in Table I. As there are different types of methodologies proposed by distinct researchers, in this paper, Table II shows several performance metrics of the proposed models to summarize the significant contributions of the corresponding authors and make a comparison of their used models.

TABLE I: Different Types of Data Sources

Source of data	The number of research investigations	Amount (%)
Data set of Independent recruitment of human participants	73	45.3416
University of California, Irvine, School of Information and Computer Science, ML Repository	40	24.8447
The Parkinson's Progression Markers Initiative data set	23	14.2857
PhysioBank database	12	7.45341
HandPD dataset	4	2.48447
mPower database	2	1.24223
Collection of postmortem data	1	0.62111
Commercial database	1	0.62111
Obtained at different institution	1	0.62111
From another research project	1	0.62111
Using data from the author's own institution's database	1	0.62111
Others (1 Seoul National University Hospital;1 collected from participant information)	2	1.24223

TABLE II: Machine Learning Models are Evaluated Using Performance Indicators

Metrics of performance	Meaning	Number of investigations
Accuracy	(TP+TN)÷(TP+TN+FP+FN)	94
Sensitivity (Recall)	TP÷(TP+FN)	65
Specificity (True negative rate (TNR))	TN÷(TN+FP)	54
AUC	The area under the Receiver Operating Characteristic (ROC) curve in two dimensions	48
Precision (PPV)	TP÷(TP+FP)	25
Precision (NPV)	TN÷(TN+FN)	6
F1 score	2×{(Precision×Recall) ÷(Precision+Recall)}	15
Others (kappa; error rate; confusion matrix; FPR (False positive rate); FNR (False Negative Rate))	N/A	12

TP: True Positive; TN:True Negative; FP:False Positive; FN:False Negative, PPV :Positive predictive value,NPV: Negative predictive value, AUC: Area under the ROC Curve

III. Source of Data & Performance Metric of the Included Studies

Reference [6] developed a low-cost and straightforward clinical tool that uses the Microsoft Kinect v2 sensor to extract postural and kinematic characteristics to identify and score Parkinson's disease. Thirty participants were enlisted for the current study: sixteen Parkinson's disease patients graded using MDS-UPDRS and fourteen healthy matched subjects. They gathered and examined three major motor tasks to explore the upper and lower body's motor abilities: (1) walking, (2) finger tapping, and (3) foot tapping. Following selection of primary features, several classifiers based on Artificial Neural Networks (ANN) and Support Vector Machines (SVM) were trained and tested to find the optimal answer. They discovered, the ANN classifier had the best results, with 89.4 percent accuracy with just nine features in diagnosing Parkinson's disease and 95.0 percent accuracy with just six characteristics in grading the severity Parkinson's of disease. The foot-tapping and the finger study findings of the research revealed that SVM employing the collected characteristics could identify healthy people vs. Parkinson's disease patients with high accuracy, reaching 87.1 percent. The classification findings between mild and intermediate Parkinson's disease patients revealed that to distinguish, the foot-tapping qualities were the most representative (81.0 percent of accuracy). The findings of this research demonstrated how a vision-based system with a cheap cost might identify subtle occurrences involving PD. Their results imply that the suggested instrument can assist medical experts in assessing and grading Parkinson's disease patients in a real-world medical context.

Reference [7] studied if the structural connection strength between subcortical areas, as described by a count of streamlines (NOS) obtained by tractography, It could be used to categorize multiple system atrophy (MSA) and Parkinson's disease patients on a single patient basis. To see how well diffusion tensor-derived measurements and NOS discriminate, the performance of subcortical FA and MD in terms of categorization was also investigated. They rebuilt the white matter pathways between 18 subcortical regions from a sample of 54 healthy restraints, 31 MSA sufferers, and 65 Parkinson's disease patients using diffusion-weighted images collected in a 3T Magnetic resonance imaging (MRI) scanner using probabilistic tractography. The difference in NOS between regions of the subcortical was examined between groups and employed as a criterion in a ML system.MSA connections between the putamen, pallidum, ventral diencephalon, thalamus, and cerebellum were reported to have reduced NOS and Parkinson's disease (PD). The overall accuracy of the classification procedure was 78 percent, with 71 percent of MSA participants being correctly diagnosed and 86 percent of PD patients being correctly classified. The characteristics of NOS exceeded the competition FA and MD in terms of discriminating performance.Their findings suggest that tractography-generated structural connections can accurately discriminate MSA and PD patients. Furthermore, NOS measurements determined via tractography may be more successful in detecting MSA than diffusion tensor-derived metrics.They discovered that the structure of the WM connection between the basal ganglia and the cerebellum in MSA patients is diminished when

compared to controls and PD patients in their study. Their findings also suggest that these connection measurements may be capable of accurately distinguishing at the individual patient level, comparing MSA and PD patients, underscoring the method's potential application as a differential diagnosis tool.

Reference [8] In this study, employed a SensFoot V2 wearable inertial device to collect 30 healthy subjects' motor data, 30 persons with 30 people and “H with Parkinson's disease while executing activities from the MDSUPDRS III for the evaluation of the lower limbs. The most critical and non-correlated retrieved parameters were chosen for inclusion in a characteristic set that can differentiate among the three types of people. A comparative classification research was conducted using three supervised machine learning algorithms. The approach was able to distinguish between healthy and sick people, we found in that paper specificity and recall of 0.967, and within a three-group categorization, people with IH may be classed as a separate class, we also found their accuracy is equal to 0.78. As a result, the approach might assist the doctor in objectively assessing Parkinson's disease.Furthermore, Detecting IH in conjunction with changes in motor parameters could be a non-invasive two-step strategy for examining Parkinson's disease at its earliest stages. Their study looked into how inertial sensors on the feet are used to make acquisitions while doing MDS-UPDRS III scale tasks. They discovered significant motor characteristics that might be used to distinguish between healthy persons, people with idiopathic hyposmia, and Parkinson's disease patients [9]. Individuals completed four motor activities from the MDS-UPDRS III scale as part of an experimental procedure, that is frequently accustomed to assess Parkinson's disease patients during neurological exams.The data was captured and sent to a personal computer, where it was filtered and transformed using algorithms that work to provide 23 variables per limb that may measure individuals' motor ability.A significance and correlation analysis was used to generate a sufficient feature set for the final classification stage [9]. Numerous comparisons were made in this study, including the application of three distinct supervised ML algorithms and they are SVM, RF, and NB to three datasets and these are 2C60, 2C90, and 3C90, for categorization into two or three groups, using data from one or both limbs. The results show that the non-obtrusive method utilized in this study allows us to accurately and precisely categorize PD patients and HC within a two-group classification system [8].

Reference [9] demonstrated a technique for automatic recognizing instances of tremor associated with Parkinson's disease using IMU data collected by a smartphone gadget. They introduced a Multiple-Instance Learning technique, in which an individual is represented by an unsorted bag of accelerometer signal segments and a single tremor annotation provided by an expert. Their solution coupled deep feature learning with a pooling system that can be learned step capable of identifying significant instances inside the topic bag while still being teachable end-to-end. They tested their method on a freshly presented dataset of 45 participants, which contained accelerometer signals gathered totally in the field. The research' good classification results show that the proposed technique may effectively traverse the in-the-wild recording's noisy surroundings.They exhibited a system for identifying binary tremors in the field using accelerometer data, a bag of acceleration signal segments and a single tremor label are used to represent each individual.To identify the essential parts inside each bag, the researchers employed a deep multiple-instance learning technique with feature extraction and a pooling scheme inspired by the attention mechanism.Extensive testing on a dataset of 45 individuals shows that the proposed technique can recognize such situations and, as a result, effectively manage the recorded signals' in-the-wild environment.Furthermore, relying solely on the supplied coarse subject-level annotations, their technique can be trained fast, addressing the issue of poor supervision.Finally, compared to the alternatives, it results in much improved performance.

Reference [10] employed magnetic resonance imaging (MRI) to evaluate the performance in diagnostics of convolutional neural networks in deep learning in differentiating each sample parkinsonian sickness.The institutional review board approved this retrospective clinical trial and waived the requirement for written informed consent.Between January 2012 and April 2016, 419 persons (125 with Parkinson's disease (PD), 98 with progressive supranuclear palsy (PSP), 54 with multiple system atrophy with severe parkinsonian symptoms (MSA-P), and 142 normal subjects) had midsagittal T1-weighted MRIs. To solve the issue of overfitting associated with DL, All participants were randomly assigned to one of two data sets: training (85%) or validation (15%), both of which included the same proportions of ill and healthy people. They used a single midsagittal T1-weighted MRI and a training group to train the CNN to distinguish between parkinsonian disorders in order to eliminate disparities between projected output probabilities and clinical diagnosis; they then applied the learned CNN to the data set for validation. The subjects were categorized as having a parkinsonian disease or a typical situation based on the final detection made by the trained CNN, and the CNN's performance in diagnostics was evaluated.Diagnostic performance accuracies were 96.8, 93.7, 95.2, and 98.4 percent for PD, PSP, MSA-P, and normal patients, respectively. For discriminating between the four circumstances (PD, PSP, MSA-P, and normal people), the areas under the receiver operating characteristic curves were 0.995, 0.982, 0.990, and 1.000, respectively. As proven, MRI allows for extremely exact distinction of parkinsonian illnesses because to deep learning like CNN.

Reference [11] introduced a Performance Weighted Ensemble Classification model. Their hypothesis was evaluated by comparing Healthy Control participants (HC) to people who have Parkinson's disease (assuming both PD and SWEDD labeled people to be in the same class). For various biomedical test groups, including Cerebro Spinal Fluid (CSF), RNA, and Serum tests, as well as pre-processed neuroimage features (Voxels-As-Features and a list of defined Morphological Features) from PPMI database subjects, their model combined Support-Vector-Machine (SVM) with linear kernel classifiers.

TABLE III: SUMMARIZES THE LITERATURE REVIEW WE BRIEFLY DISCUSSED IN THE EARLIER SECTION

Objectives & Ref.	Source of data	Method(s) of machine learning, splitting strategy, and cross validation	Findings	Number of subjects (n)
PD is differentiated from HC by its classification [6]	Participants' data was gathered	ANN using 5-fold cross-validation, SVM (linear, quadratic, cubic, Gaussian kernels)	**ANN**: Sensitivity = 90.0% Specificity = 99.0% Accuracy = 95.0% **SVM**: Sensitivity = 87.0% Specificity = 91.8% Accuracy = 89.4%	30; 14 HC + 16 PD
Classification of Parkinson's disease from MSA [7]	Participants' data was gathered	Validation using SVM with leave-one-out cross	Sensitivity = 83.33% Specificity = 74.19% Accuracy = 77.17%	62 PD +151; 59 HC + 30 MSA
PD, HC, and IH classification [8]	Participants' data was gathered	Random forest, nave Bayes, and SVM-polynomial with 10-fold cross validation	**HC + IH vs. PD, random forest:** Precision = 98% Recall = 93% Specificity = 98% F-measure = 96% Accuracy = 97% **HC vs. PD, naïve Bayes or random forest:** Precision = 96% Recall = 96% Specificity = 96% F-measure = 96% Accuracy = 96% **Multiclass classification, random forest:** Precision = 78% Recall = 77% Specificity = 88% Accuracy = 78%	30 PD + 30 IH+ 90; 30 HC
PD is differentiated from HC by its classification [9]	Participants' data was gathered	RkF or Deep-MIL-CNN with LOSO	**Repeated k-Fold (RkF):** Precision = 96% Sensitivity = 85% Specificity = 98% F1-score = 90% **Leave One Subject Out (LOSO)**: Precision = 98% Sensitivity = 90% specificity = 98% F1-score = 95%	45; 14 HC + 31 PD
PD, PSP, MSA-P, and HC classification [10]	Collected from participants	CNN using an 85:15 train-validation ratio	**PSP:** Sensitivity = 84.6% Specificity = 96.0% AUC = 98% Accuracy = 93.7% **HC:** Sensitivity = 100.0% Specificity = 97.5% AUC = 100% Accuracy = 98.4% **PD:** Sensitivity = 94.4% Specificity = 97.8% AUC = 99% Accuracy = 96.8% **MSA-P:** Sensitivity = 77.8% Specificity = 98.1% AUC = 99% Accuracy = 95.2%	98 PSP + 54 MSA-P+ 125 PD+ 419; 142 HC
PD is differentiated from HC by its classification [11]	Database of the PPMI	10-fold stratified cross-validation CNN (LENET53D, ALEXNET3D)	**ALEXNET3D**: AUC = 98% Accuracy = 95%	448 PD+642; 194 HC

Their suggested technique employed all available data sources and picked the most discriminating traits. Classification rates of up to 96 percent were achieved using this performance-weighted ensemble classification model. This research had a number of noteworthy advantages: a robust classification method based on the use of -Stable distributions that includes an effective intensity normalization technique; a classification scheme that improves the performance of models created for each set of

markers; a multimodal CAD system with many heterogeneous data sources and an ensemble classifier that selects the most reliable features from the input sources. Image-based classifiers are the only ones that work (VAF and Morp) with accuracies on average 94.38 and 90.64 percent, respectively, were determined to be adequate for final ensemble classification. When the biomarkers, as mentioned earlier, were added in their multimodal studies, they received higher ensemble classification results.

IV. Comparison Between Traditional ML and Deep Learning Model

Table III shows how TML algorithms like SVM work [12], Bayes or Random Forest [13], the performance metrics, along with the accuracy of detecting PD is, less than modern deep learning approaches such as CNN [14] and other architectures. For example, using SVM with cross-validation-leave-one-out [7], the architecture only successfully classifies 77 inputs out of 100, resulting in other metrics like sensitivity (83%) and specificity (74%), insufficient to identify such fatal disease in the case of the medical sector. Moreover, by using several hyperparameters like linear, quadratic, cubic, Gaussian kernels, [6] achieved 89% accuracy and 87% sensitivity and 91% specificity. On classification between PD, HC and idiopathic hyposmia (IH) [8], Naïve Bayes and Random Forest algorithms performed better than SVM for 96% accuracy with other metrics such as specificity, precision and F1-measure at the same rate. Nevertheless, multiclass classification random forest shows a substandard result with an average of 80% on these same metrics.

However, deep learning shows a significant and well-grounded result in detecting PD than traditional machine learning algorithms. Convolutional Neural Network [15], also known as CNN, is one of the leading deep learning architectures to extract core features from several types of inputs. ALEXNET3D [11] with 10-fold stratified cross-validation shows significant results in classifying PD from the HC dataset by providing 94% accuracy and 98% AUC. Furthermore, for multiclass classification from the datasets of PD, PSP, MSA-P and HC, CNN shows 96%, 94%, 95% and 98% accuracy, respectively, with an average of higher than 95% rate in sensitivity, specificity, and AUC. Apart from this, a different approach was taken by Papadopoulos [10], where CNN is applied using Multiple-Instance Learning (MIL) with two distinct implementations – a. LOSO and b. RkF. Deep-MIL-CNN achieved the most promising performance metrics with LOSO, such as 98% accuracy, 95% F1-score, 90% sensitivity, and 98% specificity. Again, the mentioned architecture with Repeated k-Fold (RkF) illustrates significant results, such as 96% precision, 85% sensitivity, 98% specificity, and 90% F1-score.

Based on the experimental result, it can be understood that the DL model outstrips traditional machine learning algorithms by successfully detecting and classifying PD diseases. However, such deep learning models' success largely depends on their internal architecture, which is capable enough to extract valuable features or patterns from the inputs than others. Nevertheless, recent research shows that these deep learning models are vulnerable to several adversarial examples. For example, [15] and [16] demonstrate how distinct adversarial examples created by several crafted noises known as perturbations can affect the inner architecture of such state-of-the-art DL models and hamper the classification accuracy, which raises a question on the application of such models.

V. Conclusion

Parkinson's disease caused severe damage to the life of the infected people, especially for aged adults. However, it can be cured to a great extent if a proper diagnosis is performed early. Hence, machine learning models can be a great asset to aid physiologists in effectively classifying PD. This review article illustrated some of the significant contributions for detecting PD by using ML models. Furthermore, to our knowledge, this is the first work to present a comparative analysis between the traditional machine learning (TML) algorithms and deep learning (DL) algorithms, based on the experimental results of earlier studies. Therefore, the deep learning models can be potential enough to detect PD at this stage.

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M.T. Ahmed is currently pursuing his M. Sc. Engineering degree in Computer Science and Engineering (CSE) from the Department of Computer Science and Engineering, Rajshahi University of Engineering Technology (RUET), Bangladesh. He obtained his B. Sc. Engineering degree in CSE from the Department of Computer Science and Engineering, Rajshahi University of Engineering Technology (RUET), Bangladesh in 2018. He is currently working as Lecturer in Department of Computer Science and Engineering, Bangladesh Army University of Science and Technology (BAUST), Saidpur, Bangladesh since 08th December, 2019 to Date. His research focuses on data mining and machine learning.

M. N. I Mondal received BE Degree in EEE from the Department of Electrical & Electronic Engineering, RUET Bangladesh in 2000 (Exam. of 1997, Session 1993 – 94), ME degree in Information & Communication Technologies (ICT) from the School of Engineering and Technology, Asian Institute of Technology, Thailand in 2008 and Ph.D degree in Information Engineering from the Department of Information Engineering, Hiroshima University, Japan in 2012. He joined as a lecturer to the Department of Computer Science & Engineering, RUET in 2001. In 2004 and 2013, he became Assistant Professor and Associate Professor in the same Department respectively. From March, 2012 to September, 2012 and from May, 2013 to April, 2014, respectively he was Visiting Research Scholar and Specially Appointed visiting Lecturer in the Department of Information Engineering, Hiroshima University, Japan. He joined as a Professor in June, 2015 in the same Department. He has been serving as a CISCO instructor since 2006. He has published his contributions extensively in journals, conference proceedings. He served as an Organizing Chair, a PC member, reviewer and sub-reviewer for many Journals and Conferences such as Journal of Foundation of Computer Science, Journal of Communication and Computer, International Journal of Networking and Computing, IEICE, APDCM, PDP, ICNC, CANDAR, IJPEDS, ICPP and so on. He is an IEEE Senior member (93455891), Joint Secretary IEEE Computer Society (CS), Bangladesh Chapter & Ex-Com member, IEEE CS BD. Also he is a Founder Chairman, Bangladesh Computer Society (BCS), BCS Rajshahi Divisional Branch Committee (Member No. 02578) and a Fellow (Fellow No. F/10973) of Institution of Engineers, Bangladesh. Mr. Mondal is CISCO Certified Instructor (Academy ID: 6174641). He has organized many reputed International and National conferences, workshops, Symposiums and Programming Contests.

D. Gupta is currently pursuing his M. Sc. Engineering degree in Computer Science and Engineering (CSE) from the Department of Computer Science and Engineering, Rajshahi University of Engineering Technology (RUET), Bangladesh. He obtained his B. Sc. Engineering degree in CSE from the Department of Computer Science and Engineering, Rajshahi University of Engineering Technology (RUET), Bangladesh in 2019. He is currently working as Lecturer in Department of Computer Science and Engineering, Bangladesh Army University of Science and Technology, Saidpur, Bangladesh. His research focuses on computer vision, generative adversarial networks and deep learning.

M. S. Ali received Bachelor of Science In Computer Engineering Degree from American International University-Bangladesh (AIUB), Fall 1999 (Convocation 2002). Master of Engineering degree in Electronic Engineering from Department of Computer and Electronics Engineering, Chonnam National University, South Korea in 2007, PhD. degree in Nano/IT Engineering from Seoul National University of Science and Technology, South Korea in 2013. Assistant System Manager, Computer Bazaar Network (CBNet), Dhaka Bangladesh from 2000 to 2001.He worked as Assistant Maintenance Engineer to Board of Intermediate and Secondary Education, Comilla, 2001 to 2003.Programmer, Ministry of Education, Bangladesh, 2003 to 2005.Software Engineer (R&D), MUSE R&D Inc. South Korea, 2008 to 2009.Project Manager (R&D), Solution Division, ActsOne Co., Ltd., Seoul, South Korea in 2013.He joined as an Assistant Professor, Uttara University (UU), Bangladesh , 2014-2015.He joined as Assistant Professor, BAUST, 2015 to 2021.He has been serving as an Associate Professor, Dept of CSE, BAUST since 2021.He has published his contributions extensively in of various domestic and International journals, conference proceedings and Symposium.Fellow of Bangladesh Computer Society, F00203.He is a Life Member (M32422) of the Institution of Engineers, Bangladesh (IEB), From 2019 to 2020 he served as a Technical Committee Member of International Electronics Communication Conference (IECC).He has been serving as a Technical Committee Member of International Conference on Electronics, Communications and Control Engineering (ICECCE) since 2018 to Date.