Deep Learning for Fault Diagnostics in Bearings, Insulators, PV Panels, Power Lines, and Electric Vehicle Applications - The State-of-the-Art Approaches

Sundaram, K. Mohana; Hussain, Azham; Sanjeevikumar, P.; Holm-Nielsen, Jens Bo; Kaliappan, Vishnu Kumar; Santhoshi, B. Kavya

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SPECIAL SECTION ON EVOLVING TECHNOLOGIES IN ENERGY STORAGE SYSTEMS FOR ENERGY SYSTEMS APPLICATIONS

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Deep Learning for Fault Diagnostics in Bearings, Insulators, PV Panels, Power Lines, and Electric Vehicle Applications–The State-of-the-Art Approaches

K. MOHANA SUNDARAM[1], AZHAM HUSSAIN[2], (Member, IEEE), P. SANJEEVIKUMAR[3], (Senior Member, IEEE), JENS BO HOLM-NIELSEN[4], VISHNU KUMAR KALIAPPAN[5], AND B. KAVYA SANTHOSHI[1]

[1]Department of Electrical and Electronics Engineering, KPR Institute of Engineering and Technology, Coimbatore 641407, India
[2]School of Computing, Universiti Utara Malaysia, Changlun 06010, Malaysia
[3]CTIF Global Capsule (CGC) Laboratory, Department of Business Development and Technology, Aarhus University, 7400 Herning, Denmark
[4]Department of Energy Technology, Aalborg University, 9220 Aalborg, Denmark
[5]Department of Computer Science and Engineering, KPR Institute of Engineering and Technology, Coimbatore 641407, India

Corresponding author: K. Mohana Sundaram (kumohanasundaram@gmail.com)

ABSTRACT Deep learning (DL) is an exciting field of interest for many researchers and business. Due to a massive leap in DL based research, many domains like Business, science and government sectors make use of DL for various applications. This work puts forward the importance of DL and its application in a few critical electrical segments. Initially, an introduction to Artificial Intelligence (AI) and Machine Learning (ML) is presented. Then the need for DL and the popular architectures, algorithms and frameworks used are presented. A summary of different techniques used in DL is outlined, and finally, a review on the application of deep learning techniques in some popular electrical applications is presented. Five critical electrical applications, namely identification of bearing faults, hot spots on the surface of PV panels, insulator faults, an inspection of power lines and Electric vehicles have been considered for review in this work. The primary aim of this work is to present chronologically, a survey of different areas in which it applies DL along with their architectures, frameworks and techniques to provide a deeper understanding of DL for widespread use in real-time applications.

INDEX TERMS Artificial intelligence (AI), deep learning (DL), machine learning (ML), power distribution faults, power system faults, fault diagnosis.

ACRONYMS USED

AI	– Artificial Intelligence
AE	– Auto Encoder
AFT	- Alternate Finger Tapping
ANN	– Artificial Neural Network
AR	– Augmented Reality
BEV	- Battery Electric Vehicles
BP	– Back Propagation
BPTT	– Back Propagation Through Time
BSFC	- Brake Specific Fuel Consumption
CAP	– Credit Assignment Path
CAV	- Connected and Automated Vehicle
CDBN	– Convolutional Deep Belief Networks
CWRU	- Case Western Reserve University
DCG	–Deeply Connected Genes
DCNN	- Deep Convolutional Neural Network
DSN	– Deep Stacking Network
ECMS	- Equivalent Consumption Minimization Strategy
ELM	– Extreme Learning Machine
ERM	- Empirical Risk Minimization
FCCNN	– Fully Convolutional Convolutional Neural Network
FCN	– Fully Convolutional Network
GCHEV	– Fuel Cell Hybrid Electric Vehicle
HAN	– Hierarchical Attention Network
IM	- Image Mosaicing
IMS	- Intelligent Maintenance Systems
IMU	– Inertial Measurement Unit

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KNN	– K Nearest Neighbours
LOPOCV	- Leave-One-Person-Out Cross Validation
NN	– Neural Network
NTM	– Neural Turing Machine
ODF	– Onset Detection Function
PMSM	- Permanent Magnet Synchronous Motor
RELU	– Rectified Linear Unit
SCAE	- Stacked Convolutional Sparse Auto Encoder
SDAE	- Stacked Denoising Autoencoder
SGD	- Stochastic Gradient Descent
SHEV	- Series Hybrid Electric Vehicle
SL	–Supervised Learning
SLP	– Single Layer Perceptron
SMOTE	- Synthetic Minority Over- Sampling Technique
SPHEV	- Series-Parallel Hybrid Electric Vehicle
SVM	- Support Vector Machines
UAS	- Unmanned Aerial System
UL	– Unsupervised Learning
V2G	- Vehicle-to-Grid
WPE	– Weighted Prediction Error
XAI	– Explainable Artificial Intelligence

I. INTRODUCTION

ML is paving the way for various real- time applications without human intervention [1]. They design the programs in ML in such a way that the data can be accessed, used to learn the mechanism involved in the application all by it. The learning starts with the statistics and observations in the data, followed by decision making to provide the best outcom [2]. The data like instructions or any direct experience is the key to the accomplishment of learning aim. Once the learning is complete without human help, the system makes the change of actions itself, and this helps in saving time for humans. Whenever a challenge like a fast-changing and dynamic environment is encountered, the need for the designer to foresee the problems and provide permanent solutions is bypassed by ML since the learning process is also dynamic and it happens by adapting to the changing condition [3]. Implementing ML algorithms comprises two phases, namely training and testing. There are three different methods of training ML algorithms. It classifies them into supervised, unsupervised and reinforcement learning [4]. In supervised learning, the algorithms can foresee events based on the learning carried out [5]. In unsupervised learning, it uses the algorithms when no labelling or classification of information is done [6].In reinforcement learning, the learning takes place for training data and based on choice, and there is a reward system for the right choice made. Based on the award of a reward, the machine can understand the right choice to make in a particular instance [7]. When ML algorithms populous industrial processes, vast data is required to complement the challenge of decision making. It can classify this data that has to be further put in use in ML with a specific cycle. Fig. 1 shows the life cycle of data. But in most cases, they process the data which is gathered in a stepwise manner. This data is often confused with the unwanted data termed as ''noise'' that is got from surroundings. Therefore, it becomes a tedious task to identify the original data and separate it from the noisy data. Also, because of the changing trend in environments, challenges related to fault identification based on the ML approach are imposed. These challenges pose a threat not only to the identification alone but also to the prevention aspect. Hence, reliable real-time transmission is a must avoid the threats posed by security issues [8]. In the last decade, ML has seen an enormous leap in terms of its applications in various industries.

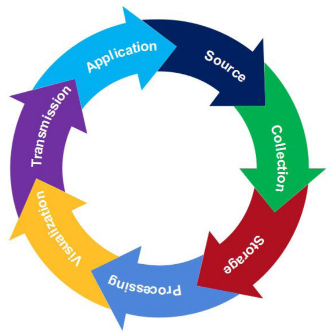

FIGURE 1. The life cycle of data.

DL is a technique under ML through which it teaches the computers to do tasks humans naturally do that with many examples and essential data in terms of images and videos [9]. Some significant areas of usage include cancer detection, object detection, speech recognition, smart city, handwriting recognition, biological image classification, natural language processing, adaptive testing, stock market analysis, plant disease detection, Optimization of microgrid, energy demand forecasting, fault diagnostics of high voltage electrical equipment, detection of hot spots on the surface of PV panel, optimization of fuel in electric vehicle applications, and many more. An application with DL requires massive data like thousands of images for the training of the model. This training could take much time and is successful when the models are trained to perform tasks incorporating and understanding data from images, sounds or texts directly without further help. Level of the accuracy of DL algorithms is high provided training is done with an extensive amount of labelled data. Also, a high-performance Graphics Processing Unit (GPU) is required to process the data rapidly [10]. DL serves as the key behind many real-time applications including automobile sector, voice recognition systems, image detection and more. The major attraction behind the use of DL is the computation method. It is made entirely automatic and can be done without human intervention. The main contributions of this paper are:

1) In this work, an introduction to AI and ML is provided, and it brings the need for DL to the limelight.

2) A summary of DL architectures and algorithms—State-of-art are summarized.

3) A review on DL approach towards the following applications is presented.

- Use of DL for identification of faults in Bearings
- DL approach to detect hot spots on PV panels
- DL for identification of faults in Insulators
- DL for inspection of power lines
- DL for Electric vehicle applications

We organize this work into the following sections. In the Section II, the need for DL algorithms is discussed. In Section III, the different architectures that are used in fault diagnosis are discussed. In section IV the application of DL algorithms to fault diagnostics of bearings are discussed. In Section V, the DL approach towards detection of hot spots on the surface of PV panels is presented. In Section VI, the use of DL for fault identification in insulators is discussed. In Section VII, DL approaches for inspection of power lines is presented and finally the application of DL in electric vehicles is discussed in Section VIII. The main conclusion drawn from this study and the scope for future study is presented in the last section.

II. NEED FOR DEEP LEARNING ALGORITHMS

A. INTRODUCTION TO AI

AI paves the way for machines to mimic the behavioral attributes of human beings. It accomplishes AI with the help of studying the working of the human brain. The learning by human beings and the way they respond to various real-time problems is the key for machines to mimic human behaviour [11]. It uses the outcome of this study as a basis for developing an intelligent software system for solving real-time problems in various applications. Some popular applications in which they mostly use AI are speech recognition, natural language understanding, and image recognition. The foundation of AI is a neuron and its functions. It is presented in [12], and it brings the use of AI in Neuroscience to the limelight. AI has seen many dimensions in applications since then. In [13], the authors have presented a detailed review of how AI helps in photovoltaic applications. AI has been a massive bid in manufacturing technology. In [14], AI implemented for Industry 4.0 it depicts based manufacturing standards. A detailed review of AI used for intelligent manufacturing is presented in [15]. Not only is AI helping the researchers of the manufacturing industry but also in fault diagnosis of rotating machinery, which is useful for mechanical and electrical design engineers to work on [16]. The concept of Smart Cities came into existence because of AI technology [17]. Thanks to AI for introducing customizable and user-friendly gadgets for implementing smart devices.

The work of humans is enormously minimized with AI. In the state-of-art developments of AI, Explainable artificial intelligence (XAI), have taken an enormous leap, especially in the last five years. It makes more-sense when machines can explain the reason for displaying a specific output. It helps the end-users to comprehend the concepts better and also feel comfortable to work with the machines. A survey of recent research in XAI has been done in [18] and [19]. So, AI has paved the way for the next generation smart technologies and various human brain replica-based applications.

B. CONCEPT OF MACHINE LEARNING (ML)

ML has been the most popular in many applications. The application of ML algorithms requires large quantity of data for triggering the process of decision making. It has published numerous literature works in ML and its applications. Some of them are presented in the following section. ML applied to it presents automated text categorization in [20], [21]. Text recognition and characterization are vital and popular applications of ML. Optimization using Genetic algorithms (GAs) has seen a new dimension with ML. For genomics and genetics, it implements ML for ease in computation [22].

The concept of ML can be understood by digging deeper into various categories of it. Fig. 2 shows the categories of ML, as mentioned in [23]. We have briefed these concepts in the following section.

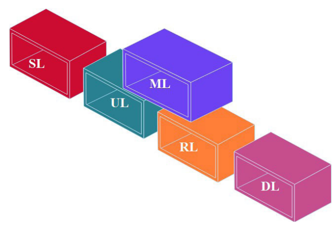

FIGURE 2. Categories of Machine learning (ML).

The abbreviations used in Fig. 2 are:
SL – Supervised learning
UL – Unsupervised learning
RL – Reinforcement learning
DL – Deep learning

C. SUPERVISED LEARNING (SL)

In this method, it inserts the already known outputs for specific inputs to train the algorithm. Usually, SL is preferred in situations where data availability is labeled. It is most extensively used principally for classification and regression [24].

Some popular algorithms under this category are ANNs and SVMs. Fig. 3 shows the block diagram of the working of the SL technique. In Fig. 3, Fig. 4 and Fig. 5, the following notations are used:

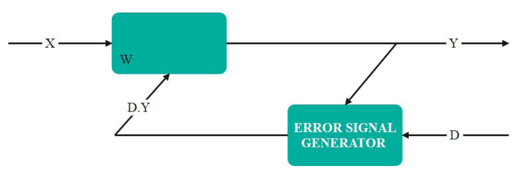

FIGURE 3. Block diagram of working of Supervised Learning (SL) approach.

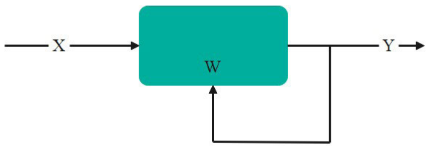

FIGURE 4. Block diagram of working of Unsupervised Learning (UL) approach.

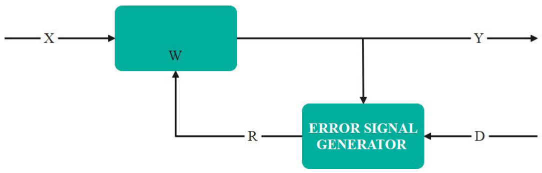

FIGURE 5. Block diagram of working of Reinforcement Learning (RL) approach.

D–Desired output
X – Input
Y – Actual output
W – Weight of the neural network

D. UNSUPERVISED LEARNING (UL)

In this method, the algorithm itself identifies patterns of unknown data sets [25], and absolutely no feedback is provided from any expert. Hence, unlabeled data is given for training. A most common algorithm is PCA, and they primarily use it only for monitoring. Fig. 4 shows the block diagram of the working of the UL technique.

E. REINFORCEMENT LEARNING (RL)

In ML, a specific action of interest is chosen, and analyze it for examining any rewards, whereas RL refers to it identifies a sequence of actions which are tried continuously until the fittest one. Therefore, from previous knowledge of rewards got and the decisions taken, working of RL based algorithm develops [26]. Fig. 5 shows the block diagram of the working of the RL technique.

F. CONCEPT OF DL AND THE NEED FOR IT

DL is a buzzword in technology right now. It represents a massive leap in the way computers could learn. One of the significant challenges faced by ML algorithms is the feature extraction process [27]. When complex problems like handwriting recognition or object recognition arise, this becomes a tremendous problem. The limitations of machine learning lead to the development of DL. DL comes to the rescue for unique design problems in real-time implementation. DL works based on Single layer perception (SLP), and Multi-layer perception (MLP). DL has been developed most prominently since 2006. In DL, exploitation of multiple stages of processed non-linear information in a hierarchical pattern is done for feature learning and pattern classification. Considering, the state of art literature available, it also links DL with representation learning in which it involves a hierarchy of features. High-level concepts are got from low-level concepts and vice versa.

As per history, DL originated from Artificial Neural Network (ANN). The Multi-layer perceptions (MLPs) and Feed Forward Neural Networks (FFN) are good examples of models that inherit deep architecture. In the early 1980s, the Back Propagation (BP) has been a popular algorithm to accomplish learning of weights of these networks. But, with more hidden layers, BP method failed to work well [28]. The enveloping presence of the local optima in non-convex aim functions of deep networks proved to be the major difficulty in learning.

It employs multiple layers to construct an ANN for human intervention free execution. Now, the wholly built ANN can make intelligent choices while handling vast and complex data with ease with no expert intervention [29]. It incorporates DL because:

- Whenever human intervention is not possible (Navigation System on mars)
- When human beings cannot explain the facts (Speech Recognition, Language Comprehending)
- When the size of the problem is too large to be tackled by a human (Advertisement Matching on Facebook)
- When the solution for a problem in real-time and dynamic (Weather prediction)
- When specific solutions have to be used in particular cases (Biometrics)

One can understand the basic working of a DL algorithm through Fig. 6. An illustration of the DL approach is depicted in Fig. 7. Some commonly used DL algorithms are depicted in Fig. 8. Different ML categories have been summarized along with their highlighted characteristics are shown in Fig. 9 and the significant advantages of DL over ML is illustrated in Fig.10. With Feature engineering, the features (variables used to train the model) are constructed from the dataset. This process is automatic in automatic feature extraction. Hence feature engineering will not be required.

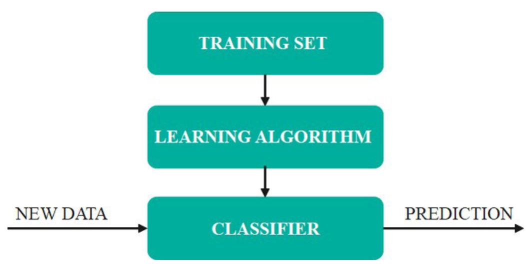

FIGURE 6. Block diagram of working of DL approach.

It inherits ML and DL from AI. This relationship can be better understood from Fig. 11 in which DL is represented as a subset of ML and ML is represented as a subset of AI.

III. ARCHITECTURES USED IN FAULT DIAGNOSIS

In the last decade, it has introduced several architectures in DL studies. Because of the new architectures developing, also found numerous problems to get immediate solutions with

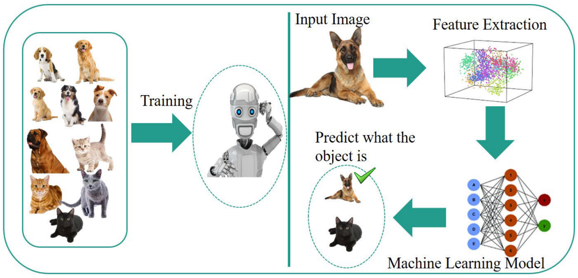

FIGURE 7. An illustration of DL approach.

FIGURE 8. Most common DL based algorithms.

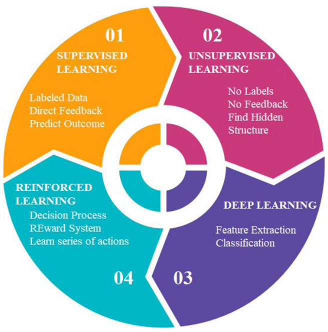

FIGURE 9. A pictorial representation of key points from different categories of ML.

FIGURE 10. Advantages of DL over ML.

ease. Thanks to the advancement in the DL era, complex problems seem easy to be solved without human expertise. In this section, it presents a brief review of the popular architectures of deep learning.

A. RECURRENT NEURAL NETWORK (RNN)

This network is the foundation for all the following network architectures and hence stands as the essential architecture in DL studies. Vital information about this architecture is that it not only has feed-forward connections but also has the feedback connections which aid in refreshing memory and previously stored data [30] Two RNN models are prevalent in literature. In Fig. 12, two varieties of RNN, along with

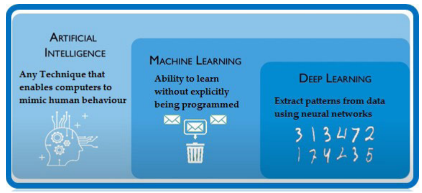

FIGURE 11. Relationship between AI, ML and DL.

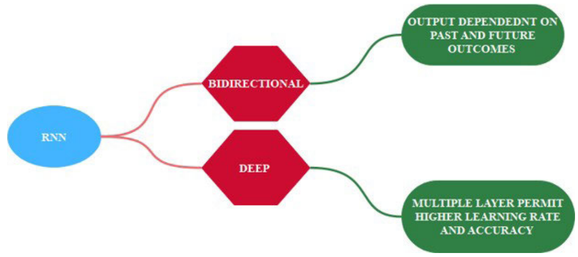

FIGURE 12. Bidirectional and Deep RNNs.

their significant features, have been depicted. It can visualize a simplified RNN architecture through Fig. 13.

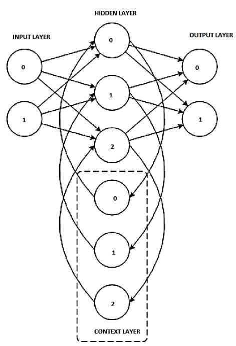

FIGURE 13. A basic RNN architecture.

B. CONVOLUTIONAL NEURAL NETWORK (CNN)

It belongs to feed-forward neural networks, in which signal flow happens without forming cycles or loops. This architecture is the most preferred one for various vision-based tasks like image recognition [31]. The execution of CNN takes place in for steps, as shown in Fig. 14 and a simple CNN architecture for five layers are depicted in Fig. 15. Here w denotes the weight of the network.

C. AUTO ENCODERS (AE)

AE operate with the backpropagation principle with an unsupervised learning environment. They are like but more flexible than Principal component analysis (PCA). It represents data with the help of hidden layers. It uses four kinds of AEs in today's scenario. Fig. 16 gives a basic outline of the kinds of AEs and the differences among them. In Fig. 17, it presents a simple representation of AE.

D. GENERATIVE ADVERSARIAL NETWORKS (GAN)

Training can be done simultaneously for two DL models. Between the two models, a fierce competition arises. One is

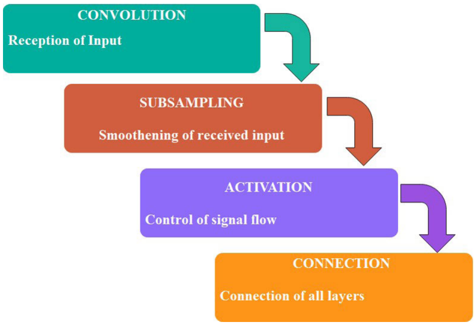

FIGURE 14. Stages in CNN.

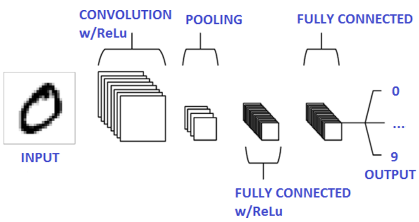

FIGURE 15. An underlying CNN architecture with 5 layers.

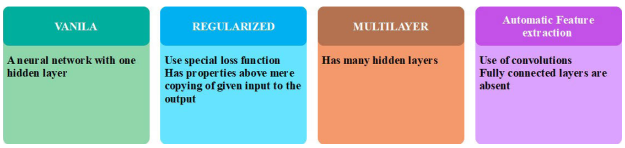

FIGURE 16. Types of AEs with their significant features.

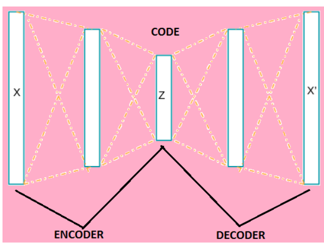

FIGURE 17. A simple representation of AE architecture.

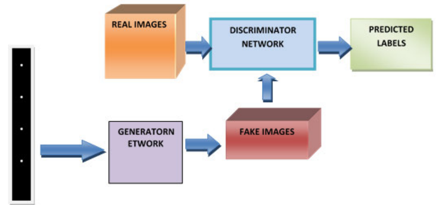

FIGURE 18. A generic architecture of GAN.

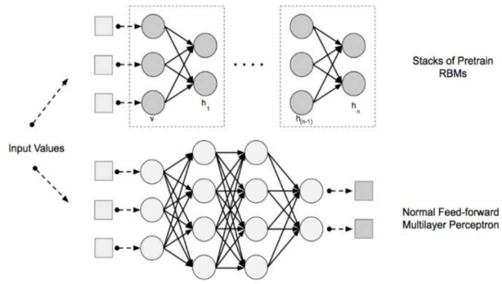

FIGURE 19. A simple layout of DBN architecture.

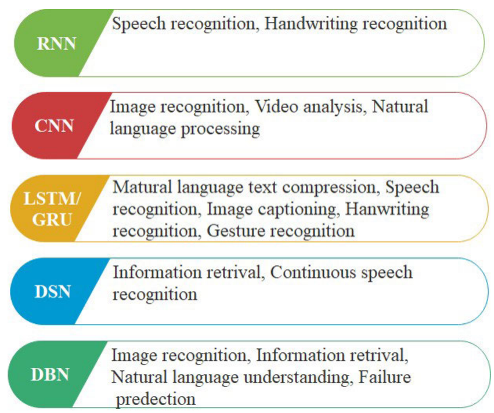

FIGURE 20. A summary of state-of-the-art architectures of DL.

termed as Generator, and call the other Discriminator. It is widely used in computer vision application image generation [32]. Fig. 18 shows a necessary representation of GAN architecture.

E. DEEP BELIEF NETWORK (DBN)

The layers of DBN architecture comprise Restricted boltzmann machines (RBMs) and feed-forward network for pre-training stage and fine-tuning stage respectively [33]. Fig. 19 describes a DBN architecture showing both RBMs and Feed-forward networks, and they're working. Fig. 20 provides a summary of literature works studied concerning state-of-the-art architectures of DL. Table 1 presents the pros, and cons of the different architectures under study.

IV. DL FOR FAULT DIAGNOSTICS OF BEARINGS

Electric machines are extensively in use for various applications. Sometimes, unfavorable operating conditions may arise. Due to such conditions, malfunction of machines occurs among which bearing faults are most common. They are responsible for up to 40% of losses. Fig. 21 shows the structure of a rolling element bearing. It contains outer race, inner race, balls and cage. The outer race is usually mounted on the cap of the motor, and the inner race holds the motor shaft. Balls are the rolling elements, and it uses the cage for limiting the distance between adjacent rolling elements [38]. The four cases of misalignment of bearings are neatly shown in Fig. 22-25. In the past decades, research towards bearing fault diagnostics has seen a significant hype since the bearing is the most susceptible component of the motor drive. This problem is being approached by establishing a physical model and analyzing the relationship between the measuring signals and the faults. This relationship can be obtained with the help of various sensors. Sensors are used to observe the vibrations [39], stator current [40], noise [41] and thermal imaging [42]. Sometimes a fusion of sensors is used to detect all or over one signal as mentioned earlier. Frequency spectral

TABLE 1. Comparison of state-of-the-art architectures used in DL.

Architecture	Pros	Cons
CNN [34]	• Can be the best for visual recognition • A segment, once identified, can be recognized anywhere throughout the flow	• Complete dependency on training data's size and quality • Prone to noise
RNN [35]	• Parameter sharing is consistent throughout the program	• Stacking into deep models is not possible • Long data cannot be interpreted accurately
AE [36]	• Resultant based on data and not on pre-defined filters • Less complex	• High training time • When training data does not represent testing data, the ambiguous output is obtained
GAN [37]	• High accuracy • Semi-supervised training is permissible	• The failure in generator or discriminator leads to total system failure • Training time is more

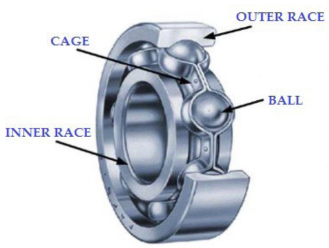

FIGURE 21. A typical structure of a rolling-element bearing.

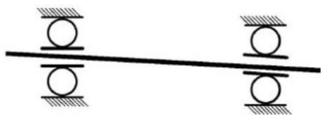

FIGURE 22. Bearing failure due to misalignment (out-of-line).

FIGURE 23. Bearing failure due to shaft deflection.

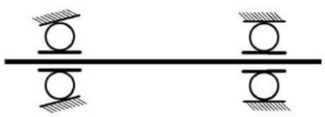

FIGURE 24. Bearing failure due to tilted outer race.

analysis performed on the measured signals aids in determining the bearing faults. The characteristics of fault depend on motor speed, the geometry of the bearing, and also the location of the fault. Many works in literature have focused on bearing fault diagnostics [43], [44], [45], [46], [47] In the last decade, there has been a continuous growth in research paper publications in DL. It presents the trend in publications cited by Google scholar for literary works in this scope in Fig. 26

The dataset formation is the first step towards the solution using the DL approach. Some essential dataset for bearing faults available in the literature have been compared and listed in table 2. Table 3 briefly summarizes the reviewed literature works that have used DL approaches for diagnosing bearing faults with the pros and cons of each approach.

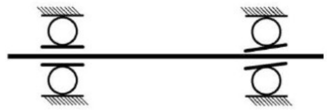

FIGURE 25. Bearing failure due to tilted inner race.

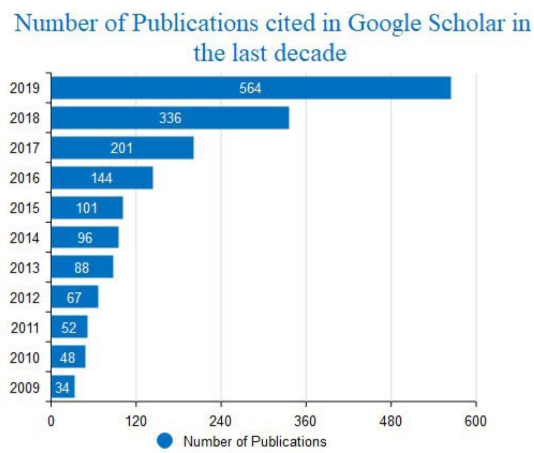

FIGURE 26. Year-wise data in publications related to Bearing Fault Diagnostics cited in Google Scholar.

V. DL APPROACH TO DETECT HOT SPOTS ON THE SURFACE OF PV PANELS

PV panels make up the best methods of providing renewable energy. Maintenance of these panels must be given utmost importance for reliable operation of PV modules. Various factors cause damage to the panels. To identify the hot spots on the solar panels, the commonly used method is aerial thermal imaging. For this purpose, many computer vision methods are used. DL approach has proven to be useful.

Several works have focused on the application of DL in PV panels [52]–[55], [1], [21], [56]–[63], [64], [65] Some literature works that address the issue of identification of the faults (hot spots on the solar panels) have been listed, and a summary has been presented in table 4.

VI. DL FOR FAULT IDENTIFICATION IN INSULATORS

Insulator faults, especially the missing ones, are most common and have adverse effects because they lead to life-threatening accidents involving high voltages. It is presented

TABLE 2. A Comparative analysis of various dataset used for bearing faults.

Name of the Data Set	Type of sensor	Frequency of Sampling	Occurrence of fault
Paderborn University [48]	Current sensor, Thermocouple, accelerometer	64 Kilo Hertz	Artificial and ageing
IMS [49]	Accelerometer	20 Kilo Hertz	Natural
CWRU [50]	Accelerometer	12 Kilo Hertz and 48 Kilo Hertz	Artificial
Pronostia [51]	Accelerometer, thermocouple	25.6 Kilo Hertz	Nature

TABLE 3. Summary of DL approaches for diagnostics of bearing faults reviewed.

Type of approach	Highlights	Pros	Cons
Convolutional Neural Network	• Preferred for 2D data • ReLu acts as a catalyst for improving Convergence speed	• Good denoising capability • Neuron connections are minimally required	• Many layers are needed for finding a complete hierarchy • The large dataset is needed
Deep Belief Network	• Composed of Restricted Boltzmann Machines • Both unsupervised and supervised learnings are permissible	• It uses layer by layer strategy of learning for network initialization. • Maximum likelihood occurrence	• Expensive computation
Generative Adversarial Network	• It was developed to generate images which replicate actual photographs • Operates in a semi-supervised manner	• No modifications needed for transfer to new applications • Deterministic bias is not introduced	• Unstable • Hard to learn
Deep Autoencoder	• Used for extraction of feature or reduction in dimensions • Makes use of unsupervised learning	• Labelled data is not needed • Robust	• Pre-training is required • It affects trainingfor fading of errors
Recurrent Neural Network	• When the output depends on computations performed earlier, this approach can be used • It can analyse 1D temporal data	• Can receive variable-length inputs • Orderly events are memorized	• Learning issues occur often

TABLE 4. Summary of literature works reviewed related to PV panel detection with DL approach.

	Technology used	Type of Detector	Outcome
[66]	Image Mosaicing	Harris corner detector	It achieved localization of faults
[67]	infrared thermography	thermal camera	Detected individual PVs within an IR image and malfunctioning PV modules
[68]	segmentation method	Thermal camera	Accurate identification of faults was got, and it identified the type of panel.
[69]	Unmanned Aerial System	thermal camera	IR imaging has been used for evaluation of thermographic behaviour and builds the image
[70]	template matching technique	computer vision	It has exploited various templates for the detection of panel extension besides identifying any defects present.

many methods based on vision in the literature as a solution to this problem. However, they cannot provide accurate results as the background of the images remains complex and accurate identification with such complexities in the images is next to impossibility. Also, multiple fault condition of the insulator is failed to be addressed by any of these novel approaches. Hence, in the following section, some State of art approaches that provide a solution to these problems is presented. Table 5 presents a summary of literature works reviewed for identification of insulator faults with a DL approach. In [71] the authors made use of 764 to adopt their novel dataset and achieved an average running time of 30ms. In table 6, a list of available dataset in fault diagnostics of insulators is listed.

VII. INSPECTION OF POWER LINES

Inspection of power lines is an ongoing process as far as power lines are concerned for supply without intermittency. Components like conductors, insulators, fitting and towers make up the power line. If there is fault occurrence any of the components, system outage occurs, and this may affect the dependent lines causing a major breakdown. Thus, it is crucial to inspect power lines frequently. There are several methods of carrying out power line inspection. Numerous publications have been done every year in power line inspection through a vision-based approach [72], [73]–[92] . The trends in publications cited by Google scholar to the same has been presented in the form of a bar graph for easier comparison in Fig. 27. The research has inclined towards

TABLE 5. Summary of the state-of-the-art literature works for identifying insulator faults using DL approaches.

Reference	Type of Fault	Method used	Detection	Identification	Primary features
[72]	The surface fault of insulator	IULBP	NP	IULBP+Rules	Texture
[73]	Missing-cap of insulator	GLCM	CGT-LBP-HSV	GLCM+Rules	Texture
[74]	The surface fault of insulator	GSS-GSO	GrabCut	Rules	Shape
[75]	Missing-cap of insulator	Up-Net+CNN	Up-Net	CNN	Deep
[76]	The surface fault of insulator	M-SA	F-PISA	Colour model	Colour
[77]	Missing-cap of insulator	SMF	Colour model	Morphology	Fusion
[78]	The surface fault of insulator	CGL-EGL	CGL	EGL	Shape
[79]	The surface fault of insulator	M-PDF	OAD-BSPK	AlexNet	Deep
[80]	Missing-cap of insulator	M-YOLO+AM	M-YOLO	Adaptive morphology	Shape
[81]	Missing-cap of insulator	R-FCN	NP	R-FCN	Deep
[82]	Missing-cap of insulator	S-AM	Saliency detection	Adaptive morphology	Fusion

TABLE 6. A list of available datasets in fault diagnostics of insulators.

Link to the Dataset available	Brief Description	Quantity
Insulator (https://github.com/InsulatorData/InsulatorDataSet)	Real-world images labeled with insulator Synthetic images labeled with defect (missing-cap)	848
Conductor (https://data.mendeley.com/datasets/n6wrv4ry6v/8)	Captured by visible and infrared cameras Subset 1 labeled with image level annotations Subset 2 labeled with pixel level annotations	8800
Insulator (https://cv.po.opole.pl/dataset1/ https://data.mendeley.com/datasets/twxp8xccsw/9)	Outdoor images taken from the ground Various lighting conditions and backgrounds	2630
Tower (https://drive.google.com/drive/folders/1UyP0fBNUqFeoW5nmPVGzyFG5IQZcqlc5)	Collected from internet and inspection videos Various types of towers and backgrounds	1300

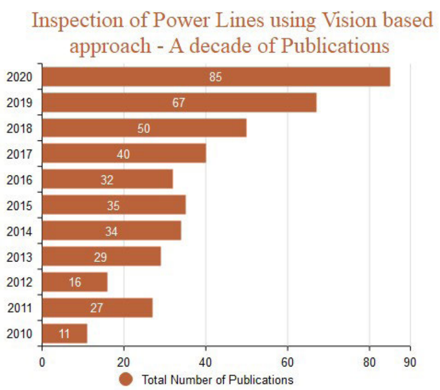

FIGURE 27. Publications indexed under Google Scholar in the last decade (2010-20).

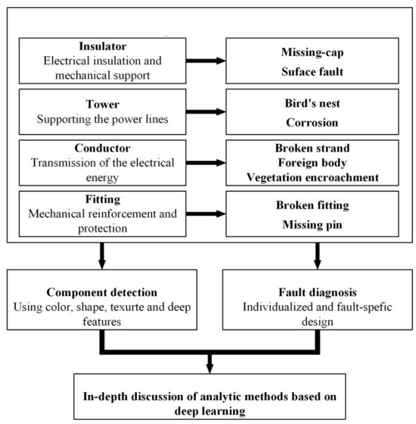

FIGURE 28. The sequential flow of inspection in power lines.

this field, and many researchers have continued to research in this area, especially since the last five years (2015-2020). A stepwise approach towards inspection of power lines with the method described in brief is depicted in Fig. 28.

VIII. DL IN ELECTRIC VEHICLE APPLICATIONS

In today's scenario, every step taken to avoid pollution is a big bonus. To avoid environmental pollution and overcome the alarming levels of temperature differences because of global warming, a compulsive motto to replace the Internal Combustion Engine (ICE) based vehicles is prevalent. As a result, several kinds of eco-friendly vehicles are being manufactured. Electric vehicles are being used extensively as a green energy option in the automobile industry. Among these, the Battery Electric Vehicles (BEV), Hybrid Electric Vehicles (HEV) and Fuel Cell Electric Vehicles (FCEV) dominate the electric vehicle market and arouse the interest of researchers. BEV stands as the most potential alternative for ICE based vehicles, although it is still immature with its traction technology and also suffers from a lack of proper infrastructure for charging [93]. As a solution towards this problem, they propose HEV with superiority in terms of its design which includes both motor and the engine.

A hybrid electric vehicle (HEV) has two Energy logging units in the form of electricity and fuel. Electrical energy is incited in a battery pack and is flooded to the traction motor for running of the drive shaft using an electro motor whereas the fuel is incited in an IC Engine to drive the same shaft through the mechanical power delivered by combustion or the same means of Electrical power from a fuel cell. HEV also depends on fossil fuel. Therefore, it cannot stand as a remedy for pollution emitted by Green House Gases (GHG) and other pollutants since it emits them from HEVs. Currently, they propose engineless configurations of FCEV. Despite the challenges posed by Fuel Cell Hybrid Electric Vehicles (FCHEV), they have gained the attention of many research

TABLE 7. Summary of literature works studied related to DL approaches applied in EV.

	Algorithm/Model/Framework	Strategy	Outcome	Benefits
[94]	Reinforcement learning (RL)	Equivalent Consumption Minimization Strategy (ECMS) is proposed	A trade-off between global learning and real-time implementation is obtained	• High computation efficiency • Low power fluctuation of fuel cell • Optimal fuel economy
[95]	Reinforcement learning (RL)	Markov decision process (MDP)	Profit is maximized for distribution system operators	• Optimal charging for EVs is achieved • Voltage Security is guaranteed
[96]	Transfer learning (TL)	TL is incorporated into DRL dependent EMS	It is proven that knowledge transfer between two HEVs could be done with TL with dissimilar structures.	Convergence efficiency is improved
[97]	Multi-Layer Perceptron (MLP)	Average torque and total harmonic distortion of back emf of a Renault model automotive named 'Twizy' are chosen as objective function with torque ripple and efficiency as constraints.	Shape optimization of Permanent Magnet Synchronous Motor (PMSM) FOR EV is obtained	Better prediction is achieved
[98]	Deep Deterministic Policy Gradient (DDPG)	Energy management strategy with rule-based reinforcement learning	Battery characteristics and optimal brake specific fuel consumption (BSFC)	• It accelerates the learning process • Better fuel economy is obtained
[99]	Deep Restricted Boltzmann Machine Bidirectional Long Short-Term Memory (DBMBLSTM)	Energy management strategy with Model Predictive Control (MPC)	A reliable forecast model for Hybrid Electric Vehicle (HEV) is achieved	Fuel consumption is reduced
[100]	Long Short –Term Memory (LSTM)	Combination of supervised and unsupervised learning	Precise forecasting of the PEVs demand	Generation of impractical travel samples is avoided. Accuracy is high (93.23%)
[101]	Deep Deterministic Policy Gradient (DDPG)	Cross-type knowledge transfer	Possibility and the outstanding characteristics of TL for energy management of HEVs has been brought to the limelight.	Shortening of development cycle is achieved with knowledge transfer among various EMS
[102]	Q Learning	Markov decision process	Forecast of EV charging station loads is done	• High speed • Accuracy • Flexibility

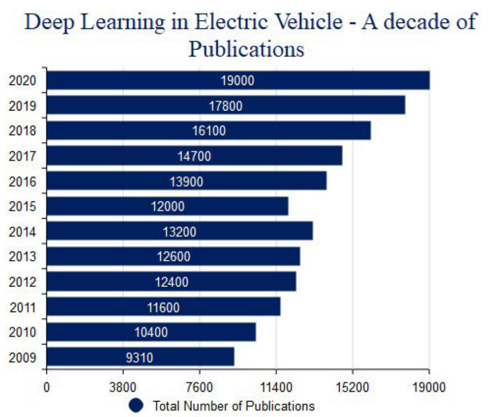

FIGURE 29. A bar chart showing a decade of publications related to DL technology in Electric vehicles.

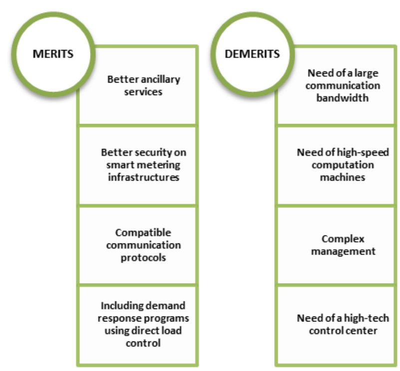

FIGURE 30. Merits and Demerits of centralized charging [119].

and development teams, intending to mitigate environmental problems caused to those mentioned above and improve fuel economy [103]. Another aspect of approach in the Electric vehicle market is the distance covered. The major challenge faced in EVs is the range that the EV can cover once it is fully charged [104]. This range has to be extended for reliable usage of EVs in the future.

The power consumption is on a larger scale for electric motors, although there are other units in EV that consume power. Hybrid and electric vehicles have proven to be propitious solutions to achieve fuel saving and emission reduction [105]. Hence the real challenge for researchers in EV lies in reducing the power consumption while carefully designing the EV for a broader operating range, i.e., distance. They have applied DL approaches towards this problem in many works [106]–[115]. Table 7 summarizes the

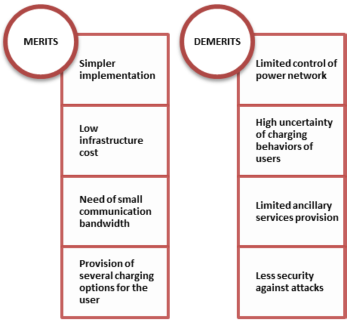

FIGURE 31. **Merits and Demerits of decentralized charging [119].**

significant literature works considered for study in this context. Fig. 29 presents a bar chart indicating a decade of publications related to DL technology in electric vehicles.

Till date, the distance covered by EV for a single time complete charge remains a challenge to researchers. It has targeted the fuel economy and power consumption optimization in areas of research in this field. So, keeping in mind, the range of coverage of a fully charged EV, the methods to charge the battery in EV have to be analyzed. Considering the charging technology used in EVs, Fig. 30 and Fig. 31 depict the merits and demerits of centralized and decentralized charging, respectively. Multimodal Deep Learning and Modular Data-Driven Architecture [116]–[118], can be used in the future as they offer promising output in the current scenario.

IX. CONCLUSION AND FUTURE SCOPE

DL approaches have been widely used in various applications. However, in this paper, five major electrical applications have been considered for review. In this work, a comprehensive review of DL approaches towards solving electrical problems like Insulator fault identification, power line inspection, PV panel hot spot detection, Bearings fault diagnostics and optimization of fuel economy in EVs has been presented. DL has proven to have phenomenal uses in different fields. The primary state- of-the-art architectures have been reviewed, and we have obtained a comparative analysis of them. An attempt to put forward a state-of-art review on literature related to five major problems in Electrical sector has been made. This will aid researchers who have an area of interest in this field.

This work can be further extended to other fault diagnostics in the electrical field. In the recent use of DL algorithms, infrequent applications including wastewater management, breast cancer detection and other non-electrical applications are being made. So, the authors would like to extend this review to explore the rare areas of application of DL algorithms in the future. This would give an outline about the various possibilities of using DL which will aid researchers in using DL algorithms in a broader dimension.

The advancement in DL has principally been achieved by exploring diverse variants in the architectures already described in literature. These variants are validated on a purely experimental basis and lack the practical approach. Thorough understanding on choosing structural features and a means to tune the parameters efficiently requires expensive setup. Cross validation approach or a validation set is used for tuning of the parameters of a model. Hence it becomes a situation that is far from reality at present.

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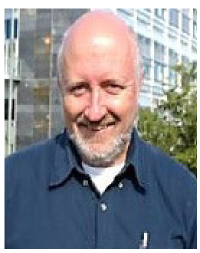
K. MOHANA SUNDARAM received the B.E. degree in electrical and electronics engineering from the University of Madras, in 2000, the M.Tech. degree in high voltage engineering from SASTRA University, in 2002, and the Ph.D. degree from Anna University, Chennai, India, in 2014. He is currently working as a Professor with the Electrical and Electronics Engineering (EEE) Department, KPR Institute of Engineering and Technology, India. He has completed funded project of worth Rs.30.79 lakhs sponsored by DST, Government of India. He has produced four Ph.D. candidates under his supervision in Anna University. He has published three books and serving as a reviewer for IEEE, Springer, and Elsevier journals. He has also published around 47 articles in international journals. His research interests include intelligent controllers, power systems, embedded systems, and power electronics. He is also an Active Member of IE, ISTE, and IAENG.

AZHAM HUSSAIN (Member, IEEE) is currently the Associate Professor of Software Engineering with the UUM School of Computing. He is also the Founder and the Head of the Human-Centered Computing Research Group which is affiliated with the School of Computing, Universiti Utara Malaysia. He is also a member of the US-based Institute of Electrical and Electronic Engineers (IEEE), and actively involved in both IEEE Communications and IEEE Computer societies. He has published in the areas of software evaluation and testing, user behaviours, group collaboration, and ubiquitous and mobile technology design. He has authored and coauthored more than 200 Scopus journal publications, served as a reviewer and a referee for refereed journals and conferences on computing as well as the examiner for more than 20 doctoral and postgraduate scholars in his research areas. He received many research grants from various organisation include Ministry of Education Malaysia, Ministry of Science, Technology and Innovation, and also international grant.

P. SANJEEVIKUMAR (Senior Member, IEEE) received the degree in electrical engineering from the University of Bologna, Bologna, Italy, in 2012.

He was an Associate Professor with VIT University from 2012 to 2013. In 2013, he joined the National Institute of Technology, India, as a Faculty Member. In 2014, he was invited as a Visiting Researcher with the Department of Electrical Engineering, Qatar University, Doha, Qatar, funded by the Qatar National Research Foundation (Government of Qatar). He continued his research activities with the Dublin Institute of Technology, Dublin, Ireland, in 2014. Furthermore, he has served as an Associate Professor with the Department of Electrical and Electronics Engineering, University of Johannesburg, Johannesburg, South Africa, from 2016 to 2018. From March 2018 to February 2021, he was a Faculty Member with the Department of Energy Technology, Aalborg University, Esbjerg Campus, Denmark. He is currently working as an Associate Professor with the CTIF Global Capsule (CGC) Laboratory, Department of Business Development and Technology, Aarhus University, Herning, Denmark. He is a Fellow of the Institution of Engineers, India, the Institution of Electronics and Telecommunication Engineers, India, and the Institution of Engineering and Technology, U.K. He was a recipient of the Best Paper cum Most Excellence Research Paper Award from IET-SEISCON'13, IET-CEAT'16, IEEE-EECSI'19, IEEE-CENCON'19, and five best paper awards from ETAEERE'16 sponsored Lecture Notes in electrical engineering, Springer book. He is also an Editor/Associate Editor/Editorial Board of refereed journals, in particular the IEEE SYSTEMS JOURNAL, IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS, IEEE ACCESS, *IET Power Electronics*, *IET Electronics Letters*, and Wiley-*International Transactions on Electrical Energy Systems*, an Subject Editorial Board Member of *Energy Sources—Energies Journal*, MDPI, and the Subject Editor of the *IET Renewable Power Generation*, *IET Generation, Transmission and Distribution*, and *FACTS* journal (Canada).



JENS BO HOLM-NIELSEN was born in 1954. He received the Ph.D. degree. He is currently the Head of the Research Group of Bioenergy and Green Engineering, Department of Energy Technology, Aalborg University, Denmark. He has 30 years of experience in the field of biomass feedstock production, biorefinery concepts, and biogas production. He was a board member of research and development committees of the cross-governmental body of biogas developments, Denmark, from 1993 to 2009. He is also a Secretary and/or the Chair of NGO biogas and bioenergy organizations. He is also a Chair and a Presenter of Sustainable and 100 percent Renewables and SDG-17 goals. He experience of a variety of EU projects, an organizer of international conferences, workshops, and training programs in EU, USA, Canada, China, Brazil, India, Iran, Russia, Ukraine, and among others. His research interests include managing research, development, and demonstration programs in integrated agriculture, environment, and energy systems. He fulfilled the biomass and bio-energy research and development projects. His research interests also include biofuels, biogas, and biomass resources. He has been the EDU and Supervising M.Sc. and Ph.D. students in these research fields. He conducts training programs: international courses, training programs, and supervision for Ph.D. students and academic staff, governmental bodies, and experts in bioenergy systems.

VISHNU KUMAR KALIAPPAN received the M.Tech. degree in communication engineering from VIT University, Vellore, India, and the Ph.D. degree in computer and information communication engineering from Konkuk University, Seoul, South Korea, in 2011. He is currently working as an Associate Professor with the Computer Science and Engineering Department, KPR Institute of Engineering and Technology, Coimbatore, India, and has 13.8 years of Teaching and Research Experience. He is also an Editorial Manager with the International Society of Intelligent Unmanned System (ISIUS), South Korea. He worked the project under the Korean Aerospace Research Institute (KARI), Degu, South Korea, and the Center for Air Born System (CABS), DRDO, Bengaluru, India. He received one of the Korean prestigious Scholarship International Information Technology Admission (IITA) from Ministry of Information Technology, Seoul, from 2007 to 2012. His name has been indexed in world's popular and leading biographical data base ''Marquis Who's Who in the World'' in the year of 2014–2017. His teaching is primarily focused in the area of mobile computing, cyber security and wireless sensor networks. The focus of his research is on bio mimetic algorithms, cyber physical systems, hardware in the loop simulation (HILS), and control algorithms for unmanned aerial vehicles. He has been acted as a reviewer and an editorial member for more 50 international conference and journals.

B. KAVYA SANTHOSHI received the B.E. degree in electrical and electronics engineering from the Saveetha Engineering College (Affiliated to Anna University, Chennai), in 2010, the master's degree in business administration (human resource management) from Alagappa University, in 2012, and the M.E. degree in power electronics and drives from the Jeppiaar Engineering College (Affiliated to Anna University), in 2015. Her research interests include power electronics and renewable energy.