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A Hybrid Bee-Markov And Cat Kernel Vector Optimized Intelligent Fault Diagnosis Framework For Multilevel Inverter Systems

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Abstract: Multilevel inverters are one of the widely used modern power electronic systems, which play an important role in converting DC power into controlled AC output suitable for high-power and industrial applications. Despite their advantages in high-power systems, reliable fault diagnosis and classification in multilevel inverter structures remain challenging due to complex switching operations and signal disturbances. These effects often overlap with fault-related signal characteristics, making reliable diagnosis very difficult. To overcome this issue, this study introduces a hybrid intelligent framework called the Hybrid Bee-Markov and Cat Kernel Vector Optimized Intelligent Fault Diagnosis Framework for Multilevel Inverter Systems. To regulate switching state distribution, the proposed approach applies an optimized Bee-based Markov modulation strategy. This helps to reduce, suppress EMI effects, harmonic distortion and produce smoother output waveforms. The technique makes it possible to more clearly identify fault-specific signal components by enhancing the standard of the resultant inverter waveform. Additionally, the presence of several flaws may result in nonlinear interactions that make diagnosis more difficult. A kernel vector principal machine is used to reduce feature dimensionality and improve classification performance in order to capture these intricate patterns. The suggested framework achieves 99.5% precision, 98.5% recall, and 91.3% classification accuracy, according to experimental findings.

Keywords: Multilevel inverter systems, inverter fault diagnosis, high frequency switching effects, fault classification, electromagnetic interference (EMI**).**

I. INTRODUCTION

Multilevel inverters have attracted a lot of attention lately. They were favored in previous years because they could produce high-quality results and were less detrimental to harmonic distortion. They have a variety of uses, including power grid integration, motor drives, and renewable energy. Several appealing methods have been put out to improve Multilevel Inverters' performance and address their inherent difficulties. The fundamental methods are associated with modulation techniques, such as Pulse Width Modulation (PWM), which regulate the inverter's semiconductor switches to produce the required output.

It contributes to lower harmonics and better voltage determination. Particularly for the upper level of the inverter and the voltage levels, there are difficulties associated with the computational complexity and the requirement for real-time implementation. The high-modulation technology, such as Selective Harmonic Elimination (SHE), Model Predictive Control (MPC), and others, is introduced to address the difficulties associated with the complexities. These methods are frequently linked to the difficulties involved in putting complex control algorithms into practice, which may ultimately result in complexity [1-4].

In the multilevel inverter, there are a number of fault detections. The algorithms have been developed in such a manner that the reliability and operation of the power electronic devices are ensured. However, there are certain drawbacks of the aforementioned approaches. The mitigation of the electromagnetic interference, which has the potential to weaken, is a serious problem. The ability of the inverter and other electronic devices, which are sensitive in nature, to be in continuous operation is a serious problem. The EMI is generated due to the high rate of change of the waveform of the voltages in the inverter, which leads to the spread of high-frequency harmonics in the electromagnetic spectrum. These high-frequency harmonics interfere with the communication of the immediate surroundings, sensors, etc., and even the power electronic devices, which leads to performance deterioration or complete failure of the devices. Therefore, the reduction of EMI is of great importance. In addition, due to the nature of the operation of the multilevel inverter, where it tries to reduce harmonics, the signal is shifted to high frequency. The challenges that are related to EMI are aggravated. The highly sophisticated form of modulation, like pulse width modulation (PWM), could be employed to reduce EMI by strategically designing the voltage waveform to reduce high frequency content. However, the balance that was achieved is to reduce EMI, and optimum system performance and close control and coordination. The importance of electromagnetic interference control is the management of Fault detection of multilevel converters. Although there are different approaches that could be employed to overcome this challenge, the challenge that has been of concern and that researchers have been struggling to achieve, and engineers are still trying to achieve, is to strike the right balance between EMI suppression and efficiency.

The classification of faults is also an important aspect that plays a vital part in ensuring the efficient operation of multilevel inverters, as they have a significant impact on power conversion systems. This process helps in the identification of faults that may have occurred in the inverter, and corrective measures can be employed in a timely manner. Examining the voltage and current waveforms at the inverter's output is a frequently used technique for fault categorization. However, this approach can have noise issues, and advanced methods might need to be used for fault categorization. Moreover, multilevel inverters have complicated circuit structures, and as a result, a large number of components are employed in these inverters. This may pose problems in terms of fault classification, as faults may occur in various parts of the inverter. In addition, faults may occur in an unexpected manner, and as such, the process of fault classification may become complicated, especially when faults occur in multiple parts of the inverter. As multilevel inverter technology advances, more research has to be done in the area of fault classification for these inverters [9-12]. The identification of fault signatures in multilevel inverter systems is also a complex task due to the complexity of system structure. The complexity of fault identification in multilevel inverter systems is also due to the complex interaction between system components. The accurate identification of fault signatures in multilevel inverter systems requires an accurate analysis of various system variables. The existing techniques are also unable to provide an accurate understanding of fault causes in a multidimensional system. Therefore, there are chances of ambiguity in fault identification in multilevel inverter systems. For academics and engineers, accurately identifying fault states in multilevel inverter systems is a major difficulty. The accurate identification of fault conditions in multilevel inverter systems can be achieved by developing an integrated solution that includes domain knowledge, data analysis techniques, and machine learning tools. Such an integrated solution can help in understanding complex relationships in a system [13-15]. Even though the detection and classification of faults from multilevel inverters has advanced, there are still a number of limitations found in this study that need to be addressed in order to improve the sensitivity of the detection and the single fault signatures. The following is the study's primary contribution:

- To highlight the issue like fault detection and identification processes in multilevel inverters Optimized Bee Vector Markov Modulation removes EMI for fault signals, and smoothen output waveforms, thus the fault detection accuracy in improved.
- To overcome the fault classification issues in the multilevel inverter, a novel Kernel Cat Boost Tree Vector Event is introduced in this approach Cat Tree Event Boosting technique & Kernel vector principal machine technique are used to identifies the nonlinear synergistic behavior and captures the complex relationships among fault variable, thus the classification accuracy in enhanced.

The aforementioned contributions have been used to overcome the shortcomings of the present methodologies. The study is organized as follows: the literature review is in the second section, the suggested technique and its framework are in the third section, and the model's performance is assessed using comparative analyses in the fourth section. Conclusions and future directions are finally included in the fifth section.

II. LITERATURE SURVEY

In this study, Qinghua et al. [16] addressed condition identification in MMC-driven HVDC transmission networks through a recurrent LSTM-based deep learning architecture. The seven operational states were reproduced via electromagnetic transient modeling in PSCAD/EMTDC, enabling end-to-end learning directly from measured signal sequences and eliminating traditional feature engineering stages. It has been discovered that the LSTM approach has a 100% accuracy rate for fault detection, can classify various faults, and has a promising fault classification performance. Overfitting is a possibility when using sophisticated models like LSTMs, especially when working with scant amounts of data.

Yongming et al [17] examined a short-time wavelet entropy approach to extract the fault-related features. Initially, the optimal short-term wavelet packet analysis period is determined to ensure accurate representation of system dynamics. Additionally, by capturing their temporal patterns, the improved LSTM architecture analyzes wavelet entropy-based fault features by capturing their temporal patterns. Then, to acquire the fault diagnosis outcome based on adaptive classification, the LSTM output features are forwarded to the SVM classifier for final decision making. The usefulness of the suggested method is lastly confirmed through the MMC fault diagnosis experiment of the double-ended MMCHVDC gearbox system. The accuracy of defect detection and information extraction can be affected by choosing the window size and amount of overlap.

Longzhang et al [18] investigated the modular multilevel converter's (MMC) IGBT's open-circuit fault behaviours. A fault diagnosis technique using the three-phase ac current average to extract fault features is then proposed, along with an intelligent optimization approach for fault detection and placement. Three-phase ac current's average value is no longer zero in the presence of a defect, allowing for the detection of malfunctioning SMs. The average three-phase ac current value results in various dc bias components when the open-circuit fault occurs in the SMs of different bridge arms is considered for analysis. The fault characteristic is extracted in accordance with the average three-phase current change rule, and the fault is then identified and detected using an SVM classifier that has been genetically optimized. It could prove challenging to create precise models for MMCs that depict the behaviour during open-circuit breakdowns.

A signal analysis technique was proposed by Faisal et al. [19] to identify open-circuit defects in IGBT switches. Relative wavelet energy is a feature of a machine learning system used to detect and categorize faulty switches. After that, flip the switches in order to get the output voltage back to normal. Machine learning algorithms used to identify inverter failures include the Support Vector Machine (SVM), Decision Tree (DT), and a hybrid model of DT with XG Boost. Overfitting is a problem for the intricate SVM, DT, and hybrid models.

The single-ended fault detection method for long transmission lines of the modular multilevel converter-based multi-terminal direct current (MMC-MTDC) system using the SVM technique was proposed by Guangyang et al [20]. This method overcomes the various problems faced by the long transmission line, especially the effect of the grounding resistance and signal attenuation. In addition, the proposed method avoids the complex process of threshold setting, which is a part of the conventional protection system. In the proposed system, the wavelet transform of the measured voltage signal provides the high-frequency component, and the amplitude of the zero mode component of the signal is used as the inputs to the SVM for the classification process.

The research done by Heya et al. [21] examined a diagnosis method that includes fault identification, classification, and pinpointing. This methodology takes advantage of a pair of submodule (SM) open-circuit configurations to monitor operational anomalies. The benefits of this methodology are: (1) Different malfunctioning IGBTs will yield different distributions of SM capacitor voltages; (2) Because there are a number of SMs in an MMC, fault identification is analogous to statistical outlier analysis. A variance-driven metric, referred to as VAR, is introduced to gauge the SM capacitor voltage in relation to fault conditions. This metric allows for the identification of anomalous patterns corresponding to various fault classes. To accomplish this diagnosis procedure, quartile analysis, a statistical outlier analysis technique, is applied to the VAR data. The nonlinear nature of MMCs makes it more challenging to pinpoint faults and anomalies.

Ahmed et al. [22] addressed the issue related to the effect of open-circuit fault occurring in insulated gate bipolar transistors (IGBTs). Such a fault has the ability to interrupt the normal flow of current and hence adversely affect the overall performance. The author further indicated that this type of fault usually occurs in modular multilevel converters (MMCs). Although a number of threshold-based diagnostic techniques are proposed for fault detection in MMCs, still the need for faster and accurate fault detection techniques with respect to real-time applications persists. To overcome the difficulties encountered during signal analysis, principal component analysis (PCA) has been broadly accepted as a helpful technique to identify key features. The classification accuracy for each classifier was obtained by averaging the results over twenty trials.

Du et al [23] suggested a unique deep convolutional neural network (DCNN) and sparse representation (SR) based fault diagnostic approach for CHMLI. TPT Ao generate the HHT spectral pictures of the monitoring signals, the Hilbert-Huang transform (HHT) is initially applied. These images accurately depict the characteristics and detailed characteristics from different regions within the time frequency domain. Additionally, these spectral images corresponding to the same fault type category are subjected to an SR-based image fusion method is utilized to produce integrated feature representations, which accurately capture the complex interrelationships among the recorded signals and fault-related features. However, inadequate fault characteristics in a one-dimensional space result in poor distinguishability for conventional techniques for extracting a selected feature from signal data.

A control technique that maximizes the selection of switching sequences was introduced by Baker et al. [24] for heterogeneous battery energy storage systems interfaced with Cascaded Multi-level Inverters (CMI). The potential power electronics-dominated grids (PEDG) will require a large Battery Energy Storage System (BESS) to provide energy availability for critical voltage, load, and frequency stability. Because the number of EVs is growing exponentially, there is an opportunity to repurpose their used batteries for grid applications. When compared to state-of-the-art control systems, the case studies covered in this study demonstrate a discernible rise in heterogeneous BESS usage. However, the different states of charge (SOCs) of these battery cells limit how much of them may be used because of their short lifespan.

Sivapriya et al [25] presented for rapid cascaded MLI fault diagnostics, use the Multiscale Kernel Convolution Neural Network (MKCNN). First, instead of using raw signals, the proposed method calls for the usage of frequency domain samples. This is due to the fact that it uses the capabilities of a convolution neural network (CNN) to extract hierarchical characteristics from the images using a Short-Time Fourier Transform (STFT). Second, the MKCNN model is used to record and analyze the low-to-high-level fault features. Distinctive fault-related features are retrieved from data using convolution kernels of different sizes and resolutions. This method offers good diagnostic accuracy for single and multiple open circuits and short circuit defects, outperforming the conventional CNN. However, it is difficult to determine complementary fault characteristics using typical methodologies because of operational complexity and small switch-fault sample sizes.

From the above studies, it is clear that [16] when utilizing complex models like LSTMs, overfitting is a concern, especially when working with little amounts of data, [17] the window size and overlap percentage impact, accurately defects are detected and information is extracted, [18] making accurate models for MMCs that represent the behavior during open-circuit failures could be difficult, [19] there is a risk of overfitting with small data sets for complex SVM, DT, and ensemble models, [20] the error type is inaccurately identified by the SVM's output, and [21] MMCs usually exhibit nonlinear behavior, which makes finding flaws and anomalies more challenging. [22] Classification accuracy for each classifier was obtained as the mean over twenty independent trials.[23] inadequate fault characteristics in a one-dimensional space result in poor distinguishability for conventional signal-based feature extraction and feature selection techniques. [24] Battery cells have a short lifespan, and as a result, their various states of charge (SOCs) restrict how much of them are used. [25]. Extracting comprehensive fault characteristics using conventional methods remains difficult because of the operational complexity of the multilevel inverter systems and the limited availability of switch-fault samples. Still, several approaches exhibit certain limitations even though they provide useful solutions for fault diagnosis. The problem arises, such as limited generalization capability, model overfitting, and challenges in capturing nonlinear system behaviour, and reduced suitability for real-time applications. Therefore, the development of a more reliable and efficient method for accurate fault detection and classification in multilevel inverters is necessary.

III. A Hybrid Bee-Markov and Cat Kernel Vector Optimized Intelligent Fault Diagnosis Framework for Multilevel Inverter Systems

Multilevel inverters have received much interest because of their high capability of generating high quality output voltage and at the same time decreasing harmonic distortion. The study resorts to the most recent algorithms like Kernel Cat Boost Tree and Optimized Bee Vector Markov Modulation and Vector Event to enhance the detection and categorization of faults at multilevel inverters. It can be used to solve electromagnetic issues, interference and harmonic content the system. When compared to conventional methods, this has brought about more attention which has resulted in the appearance of several new innovative methods that are directed to improving the efficiency of such inverters and in effect, making them overcome their intrinsic difficulties. To overcome the limitations, present in the past research and enhance the accuracy. The multilevel inverter, classification and detection of multilevel systems, the Optimized Fault Detection and Classification of Bee Markov Modulation Multilevel Inverter and the one proposed is Cat Kernel Vector. These multilevel inverters are touted to have the capability of obtaining high-quality AC. waveforms, much more harmonic content is cut. to conventional two-level inverters.

The high-frequency Multilevel inverters produce switching, inherent in them. The frequencies that are electromagnetic interference (EMI). unfortunately coincide with fault signatures frequencies, blurring the detection of fault-distinctive signals. This EMI conjunction of patterns indicates the patterns of fault. in signals, which is a major problem in the area of fault. diagnosis and proper diagnosis. To overcome this issue, the Optimized Bee Vector Markov Modulation Proposed. technique systematically allocates switching states, hence, minimization of the harmonic content, reduction of EMI, and generation. smoother output waveforms. Consequently, this process decreases. the frequency content that causes interference. The later analysis of individual frequencies in. the signal determines the ones that are vital in fault detection and diagnosis, with great attention to frequency components. including the necessary fault-related data. Through optimization, this is a methodology that optimizes patterns. parameters to expand the fault signature detection ability. and at the same time mitigating the negative effect of EMI.

Moreover, there was the occurrence of more than one fault either. simultaneously or successively provokes nonlinear interactions, generating synergistic behavior that will result in unexpectedness. patterns. In order to deal with this complexity, the introduction of a was introduced. Kernel Cat Boost Tree Vector Event can be used to enhance. event cat tree boosts accuracy of classification. determining the nonlinear synergistic behavior that results due to the effect of several faults. This comprehensive approach builds event trees with a systematized depiction. some fault sequences and precursor results to point out. how evil plays with each other and produces strange fashions. This perceptive study uncovers the complex of nonlinearity and the Use of synergy due to the presence of many. faults.

A multilevel inverter, through a combination of several voltage, combines several voltages. sources, generates output voltage levels. However, when a fault takes place, the voltage levels and patterns formed are different. based on the location and severity of certain faults and condition. topology of itself. In turn, it is difficult to define one. fault signature is an important task and precise. isolation and classification are not an easy task. The use of the Kernel Vector Principal Machine, the Art of apprehending. complex nonlinear fault relations, is used in determining the. most significant features to distinguish fault classes. This process and at the same time, dimensionality of the feature is reduced. space, which eventually increases the productivity of the follow-up. classifications. This advanced algorithm is a navigating algorithm. subtle complex and nonlinear patterns of fault data, effectively verifying new fault cases in terms of extracted. characteristics, at the same time as addressing different fault patterns and multiple fault scenarios. Specifically, the area of the attention of the proposed methodology is based on the finding and localization both open-circuit (OC) and short-circuit (SC) faults in multilevel inverter systems. SC faults, which involve System faults: accidental connections, are separated, and OC faults are. detected by measuring voltage and diagnostic tests to. reveal alienated elements. By addressing both types of is holistic, and as such, faults are handled holistically. diagnostic and correction solution. The overall process of the proposed Improved Fault Detection and Classification of Multilevel Inverter According to the Bee Markov Modulation and Cat. Figure 1 illustrates Kernel Vector.

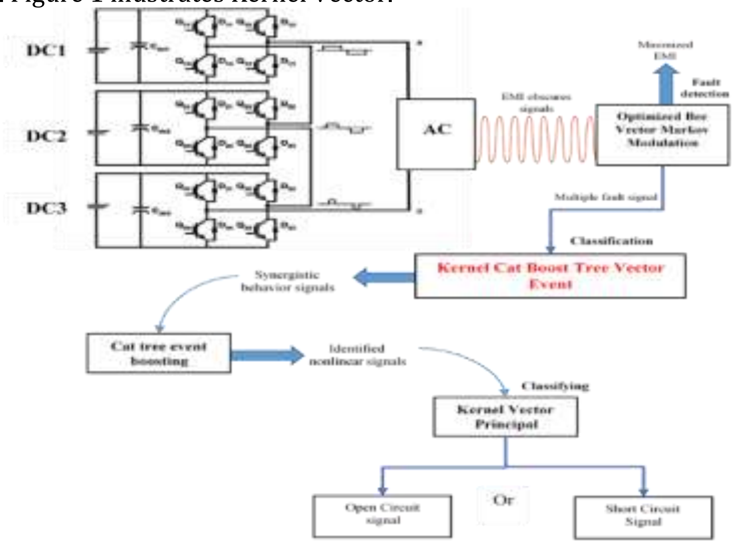

Fig. 1. Architecture of the proposed method

This study underscores the important role played by fault. detection and classification are involved in ensuring the system. dependability regarding the DC1, DC2 and DC3. Figure 1 illustrates multilevel inverter systems. It is important to constantly check the output voltage and switches. To identify an outlier, such as abnormal currents or a deviation of predicted voltage levels. These anomalies recognize errors, as open or short circuits. The passage refers to the high-frequency switching difficulties in multilevel. inverters which make fault detection worse and give rise to. electromagnetic interference (EMI). The "Optimized Bee The methodology is a Vector Markov Modulation" methodology. new style of intentionally reducing harmonic material, eliminate EMI noise, and rearrange systematically. switching states. In addition, there is the multi-level inverter device. identification of failures, especially identifying a specific one.

Faulty switch, must be a combination of techniques and approaches. Fault-tolerant Multilevel Inverter (FTMLI) Topology covers both one switch fault and multi switch faults. faults without compromising the rated voltage and power. Fuzzy The open circuit is detected and classified by Inference System (FIS). defects in Cascaded H-Bridge Multi-Level Inverters (CHMLI), thus increasing the quality and speed of fault diagnosis. The distortion of the output voltage is carried out by the Distortion Analysis. and instantaneous waveforms of the system and energized faults at open circuit are implemented and compared with pre-determined threshold. values to identify the malfunctioning devices. More information on this technique shall be given later

A. Optimized Bee Vector Markov Modulation

This modulation efficient bee vectors act as a black swan modulator to a white beam, thus producing a white beam modulation signal. Multilevel inverters play an essential role in high-power applications. However, the high-frequency switching process carried out by the multilevel inverters is high. A huge obstacle in the form of Electromagnetic interference (EMI). This is an interference to cover up fault. The interference is in the form of interference signals, which make the proper identification of the system difficult. Faults. Innovative techniques have been adopted to combat the complexities of the multilevel inverters, and one of them is the Optimized Bee Vector Markov. A good solution is a modulation technique. Multilevel inverters are normally in the state of high productivities due to the high switching process involved in them. The main contributor of the high harmonic content is the same as the high levels of disruptive EMI, which occur at the same frequency as the high levels of importance in the identification of the faults. The high switching of the power devices leads to the production of harmonics in the multiple of the main frequency, which in turn leads to EMI that interferes with the fault detection, which may cover up the fault and indicate the faults in the system. The solution to this problem is the meticulous rearrangement of the switching states of the inverter. The main aim of this modulation is the reduction of the unwanted harmonics that may coincide with the fault-related frequency, thereby mitigating the interference. After the modulation, the analysis of the frequency is crucial. The analysis of the frequency is the thorough examination of the signal in the process of fault detection in order to identify the crucial fault-related frequency components. In addition to this, the method goes beyond the minimization of interference. It involves a process of fine-tuning the parameters within the system's architecture to improve the accuracy of fault detection, particularly within an environment with complex EMI. This process follows a systematic approach, incorporating modulation techniques, frequency analysis, and parameter optimization to resolve interference related to harmonic content within a multilevel inverter. This ensures accurate fault detection despite the complex EMI conditions. The Optimized Bee Vector Markov Modulation model offers a flexible approach to problem identification, diagnosis, and mitigation for multilevel inverter systems. The model incorporates energy storage, voltage management, harmonic mitigation, defect detection, and EMI reduction. With an analysis of the switching states and modulation techniques, the Optimized Bee Vector Markov Modulation model detects fault-related changes with precision. Moreover, it helps in minimizing the amount of harmonic content in voltage waveform outputs, thus improving the power efficiency in motor drives and renewable energy systems. The model offers a versatile approach to optimize modulation schemes in multilayer inverters. Algorithm 1 illustrates a pseudocode for Optimized Bee Vector Markov Modulation.

Algorithm 1: Optimized Bee Vector Markov Modulation

Input: Raw voltage signals, fault-related frequency data, and parameters related to the inverter switching process.
Output: Accurate fault-related frequency identification within the output signals of the multilevel inverter despite the occurrence of electromagnetic interference.

Step 1: Voltage signals are obtained from the output of the multilevel inverter.
Step 2: The characteristics of the obtained signal are analyzed to identify the harmonic content present within the signal, which is a result of the high number of switching transitions occurring within the inverter.
Step 3: The effect of electromagnetic interference on the signal's frequency content is evaluated, as this interference might conceal the fault-related frequencies within the signal.
Step 4: The Optimized Bee Vector Markov Modulation Strategy is implemented to modify the switching process within the multilevel inverter to reduce the harmonic content related to fault frequencies.
Step 5: The modified signal obtained from the optimized modulation process is evaluated to identify the fault-related frequencies within the signal.
Step 6: The parameters are adjusted to enhance the reliability of the fault detection process despite the occurrence of electromagnetic interference.
Step 7: The modulation process is repeated if necessary to enhance the reliability of the fault detection process.

To improve the fault diagnosis in multilevel inverters operating under EMI, the Optimized Bee Vector Markov Modulation algorithm is designed. During the inverter switching, this method first classifies the harmonic-rich outputs produced during inverter switching. Since EMI obscure important fault signatures, the modulation strategy is adjusted to suppress harmonics that overlay with fault-related frequencies. After that, frequency analysis is performed to filter relevant components related to faults. The system parameters are then adjusted to enhance the reliability of fault detection. The framework gradually enhances its ability to detect faults, even in the presence of EMI, through the refinement of the modulation and analysis stages. It is in this stage that Figure 2 illustrates the flowchart of the Optimized Bee Vector Markov Modulation process and identifies the key phases in its operation.

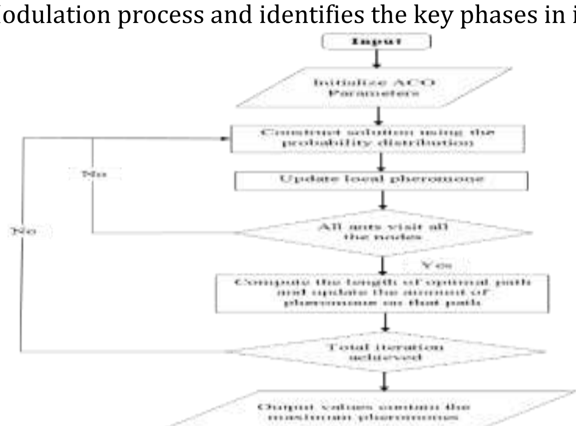

Fig. 2. Flowchart of Optimized Bee Vector Markov Modulation algorithm

In the following Figure 2, the flowchart of the Optimized Bee Vector Markov Modulation algorithm is shown. The algorithm starts with the initialization of parameters and the creation of the bee-vector population. The fitness of the vectors is determined with the intention of restricting harmonic distortion and electromagnetic interference. For the identification of fault-related patterns in the process, the modulation behavior is linked with the Kernel Cat Boost Tree Vector Event mechanism. The inverter switching states are then updated by the Bee Markov Modulation algorithm, and the positions of the vectors are adjusted based on the fitness values computed in the process, reaching convergence. For the observation of the spectral characteristics of the modulation configuration, the process is further subjected to frequency analysis. For the improvement of fault identification, the Kernel Cat Boost Vector Event mechanism is again utilized in the analysis process. The parameters are further refined in the process. The implementation details of the algorithm are discussed in the following section.

B. Kernel Cat Boost Tree Vector Event

However, the classification of faults for multi-level inverters becomes very complex when multiple faults occur, either in series or parallel, and interact with the system. Therefore, to solve the aforementioned problems, the proposed framework utilizes the Kernel Cat Boost Tree Vector Event approach, which integrates the Boost Tree model and the Kernel Vector Principal Machine. This enables the detection of non-linear relationships between the fault events, thus facilitating the reliable classification of the faults. After that, to model different sequences of faults and their outcomes for the inverter system, the algorithm generates the event trees. By analyzing the event trees, the framework identifies the interaction between the faults, considering the cases when the faults occur simultaneously or interact with each other. This provides a deeper understanding of the system, considering the combinations of the faults, and reveals the relationship between the events, which might otherwise be difficult to establish using other approaches.

The algorithm is faced with numerous complexities in the case of multi-level inverters, where multiple voltage sources are present, leading to faults that cause variations in the voltage levels. These variations are occurring due to certain factors, such as the location of the fault, the severity of the fault, and the inverter configuration. These conditions are posing difficulties in defining a unique and distinctive signature for each fault, making it complicated in identifying and classifying the faults. In this case, the Kernel Vector Principal Machine is used, as it is an advanced analytical tool that can handle the complicated relationships between different fault conditions and reveals the pattern that is not clearly evident in the process. This enhances the accuracy of fault frequency classification, even in complicated inverter operating conditions. This proposed model can be used in several fields where fault diagnosis plays an important role. In power systems, this method can be used to diagnose abnormal conditions such as short circuit, overcurrent, open circuit faults, etc. It can also be used to carry out predictive maintenance by analyzing the trends of faults over long periods of time. In the field of industry, this method can be used to monitor the process and diagnose any abnormal conditions that may cause downtime. It can also be used to diagnose irregular patterns in network traffic or activity. The general pseudocode for the Kernel Cat Boost Tree Vector Event framework is given in Algorithm 2. The flowchart for this proposed method is given in Figure 3, which shows the main phases of the method.

Algorithm 2: Kernel Cat Boost Tree Vector Event

Input: Raw fault information from multilevel inverters, including voltage information, timestamps, severity, and configuration details.
Output: Accurate and reliable classification of faults in multilevel inverter-based systems.
Step 1: Collect raw fault information from the multilevel inverter system and preprocess it to remove inconsistencies.
Step 2: Apply the Kernel Cat Boost Tree Vector Event method to recognize the non-linear relationship between fault conditions.
Step 3: Develop an event tree diagram to represent the occurrence of faults in the multilevel inverter system.
Step 4: Analyze the event structures to recognize hidden patterns and interactions of faults in the system.
Step 5: Analyze the event structures to recognize interactions among fault events.
Step 6: Identify dominant fault features using the Kernel Vector Principal Machine method.
Step 7: Refine significant features for classification.
Step 8: Performed fault classification using the refined features.
Step 9: Refine the process as needed.

The algorithmic process of analyzing the faults of multi-level inverters occurs through a series of analytical stages. To analyze the complex interactions of the fault events, the process includes data preparation, the inclusion of the fault classification process, and the development of the event trees. These event trees aid the process of understanding the nonlinear fault behaviors, which occur as a result of the different operating conditions. Due to the voltage fluctuations, the process of classifying the faults becomes complex, and the use of the Kernel Vector Principal Machine assists the process of extracting the important fault characteristics, thereby simplifying the process and enhancing the accuracy of the classification process.

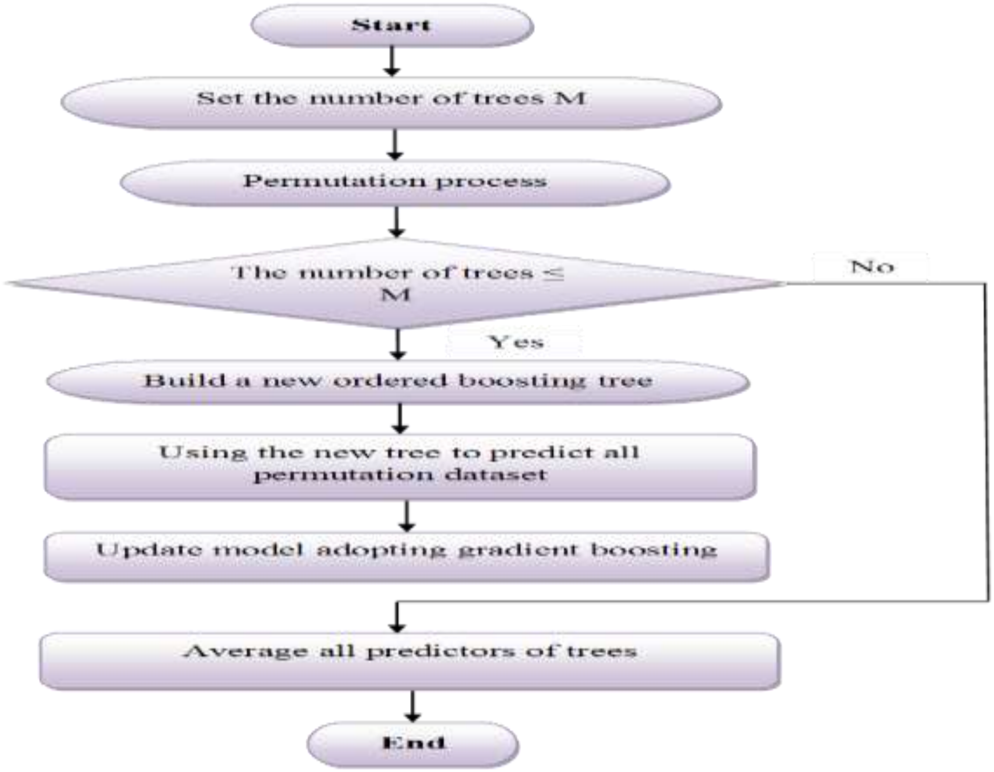

Fig. 3. Flowchart of Kernel Cat Boost Tree Vector Event

The flowchart of the Kernel Cat Boost Tree Vector Event Framework is shown in Figure 3. The initial steps begin with organizing the dataset, where the relevant attributes and class labels of the classes are positioned, and the required parameters are set. Cat Boost tree structures are then developed and enhanced with kernel functions, allowing linear relationships between the fault data to be modeled with more efficiency. To support the fault classification, process this model operate together the Vector Event approach. The framework is introduced to training and testing data in the learning stage where it can lean the patterns generated when several faults are presented in the inverter system. To illustrate the various fault sequences and outcomes the event tree structures are introduced. Parameters values are gradually adjusted for the performance improvement. The frameworks offer Kernel Cat Boost Tree strategy for identifying faults in multilevel inverter systems, after the learning process stabilizes.

From the discussion, fault identification within the high-power multilevel inverter using the defined method is introduced to rectify the increasing challenging caused by EMI. The framework introduces different kinds of techniques, within that Optimized Bee Vector Markov Modulation technique plays a main role. To limit harmonic components and reduce EMI influence that hide important fault signatures this technique rearranges the inverter switching patterns. To support accurate fault identification even under strong EMI conditions the process modulation strategies like frequency examination after modulation, and parameter adjustment. In addition to the same way the Kernel Cat Boost Tre Vector framework is integrated to assist in distinguishing various fault conditions and also strengthen the analytical stage within the inverter system. To modify fault diagnosis and classification both methodologies are introduced while addressing the challenges created by EMI. In the further section 4, comparison of proposed and performance of the method is discussed.

IV. RESULTS ANALYSIS

To understand the fault frequency of open circuit and short circuit faults, the fault detection of the multilevel inverter using the python-based analysis is discussed in this section. The open circuit fault occurs when the normal current path is interrupted, whereas the short circuit fault occurs when unwanted connections are made. The python-based tools are used for the analysis of the inverter signals. The fault classification is done in an accurate manner using the tools. In addition to the above, the implementation of the fault detection and classification algorithms in the real-time digital controller devices such as FPGA and DSPIC is considered. The fault detection and classification algorithms are incorporated in the real-time devices in order to effectively control the multilevel inverter operations. The creation tools, programming languages, and hardware limitations are considered in the study. The sophisticated algorithms are implemented in the FPGA devices. The algorithms are processed in the logic units of the FPGA devices. The algorithms are optimized in the DSPIC devices using the high-level programming languages. The algorithm optimization is carried out in the DSPIC devices, and the interrupt management is done. There is also an application for other digital controllers, such as system-on-a-chip and microcontrollers. There is also the provision of information concerning the application of these algorithms to real-time digital control settings, as the comment questions the application of the algorithms.

A. Experimental setup

Programming Language : Python
Operating System : Windows 10 (64-bit)
Processor : Intel Core i5
Memory : 8 GB RAM

B. Simulated outcomes of the proposed method

The simulation's conclusions shed light on how the system is represented and how it functions under various input and condition scenarios. These outcomes include any relevant information that helps analyze and understand the dynamics, behavior, or conclusions of the simulated system, such as numerical data or graphical representations.

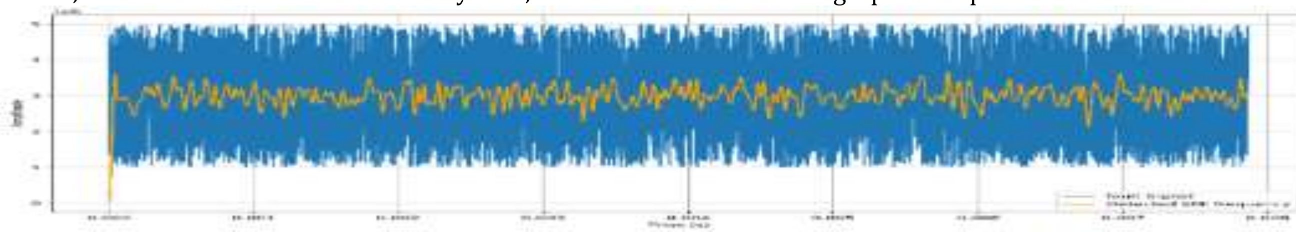

Fig. 4. EMI frequency detection.

Plotting two signals over time, the raw Signal (blue line) and the Detected BEM Frequencies (yellow line), is shown in Figure 4 signal processing imagining. The time is represented as x-axis, while the amplitude is represented as y-axis. The blue line represents the raw data, and the identified BEM frequencies are shown by the yellow line, which is the result of processing the raw signal possibly by filtering or other methods.

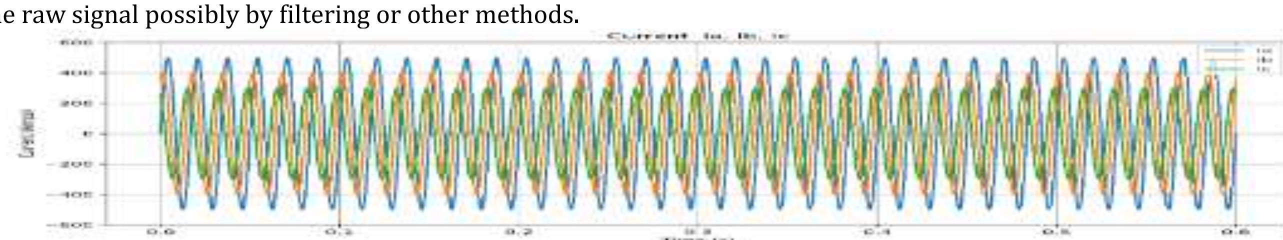

Fig. 5. 3 phase current from multilevel invertor.

Figure 5 shows a synchronized three-phase current waveform I_a, I_b and I_c generated by a multilevel inverter. Before the fault, the system's voltage output waveform spans five cycles, clearly showing the voltage magnitude and phase over time. Similarly, the current output waveform represents the system's current output before the fault, spanning five cycles and clearly showing the current magnitude and phase over time. The switch voltage waveform shows the voltage across the switch in the system before the fault, spanning five cycles and clearly illustrating the switch voltage over time. After the fault, the voltage output waveform depicts the system's voltage output, spanning five cycles and clearly showing the changes in voltage magnitude and phase over time due to the fault. The current output waveform represents the system's current output after the fault, also spanning five cycles and clearly showing the changes in current magnitude and phase over time due to the fault. Lastly, the switch voltage waveform shows the voltage across the switch in the system after the fault, spanning five cycles and clearly illustrating the changes in switch voltage over time due to the fault.

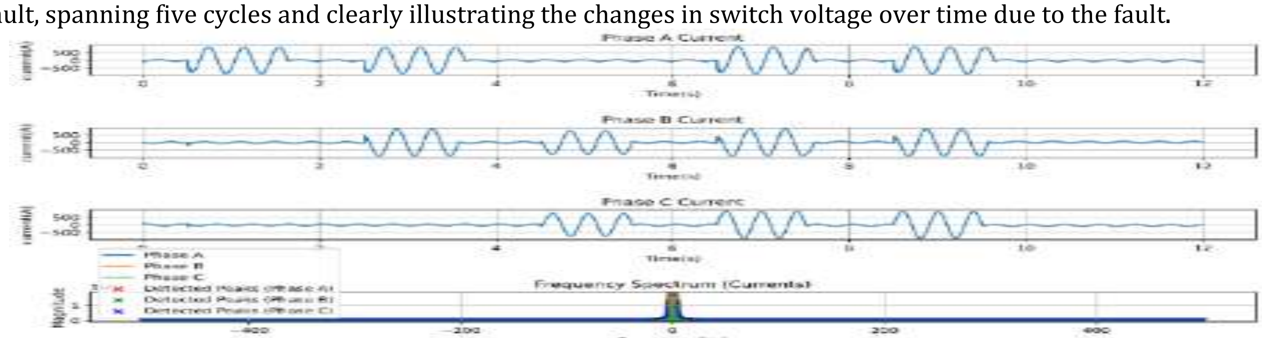

Fig. 6. Fault frequency After eliminating EMI.

Three-phase electrical currents are depicted in Figure 6 together with the associated frequency spectrum. The waveforms of the current phases A,B,C are showin in top three graphs, which show alternating current. The bottom graph analyzes the harmonic content while displaying the frequency spectrum. These graphs are essential for evaluating a three-phase power system's efficiency and performance and spotting problems like harmonic distortion.

C. Performance results of proposed method

The performance evaluation findings acquired by the suggested fault frequency classification approach will be thoroughly discussed in this section. Numerous factors, including accuracy, fault frequency, EMI frequency, execution time, phase voltage across the transformer, and system spectra following EMI reduction, have been used to assess the suggested approach. Together, these metrics assess the suggested method's precision, dependability, and efficacy. The outcomes of the suggested approach are quite satisfactory and show that it can effectively operate with multiple inverter systems. By taking into account the response time that the suggested method produced, the effectiveness of the defect detection and classification approach has been further assessed.

The outcomes of the suggested approach are quite satisfactory and show that it can effectively operate with multiple inverter systems. New algorithms have been added to the suggested approach to speed up response times. It is anticipated that the enhanced algorithms will yield a quicker response than the traditional approach. This will enhance the suggested method's capacity to operate effectively with multilayer inverter systems.

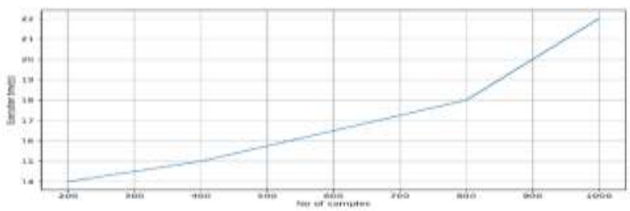

Fig. 7. Execution time of Fault classification

The proposed model has a performance with regard to Figure 7, which illustrates the execution times. The execution time peaks at 22 seconds at 1000 samples and has a minimum value of 14 seconds at 200 samples. The data's Cat Tree Event Boosting strategy gives the input value that enhances the performance. This strategy led to tremendous increase in the time of execution of the model over the samples and certain precise determination of crucial qualities.

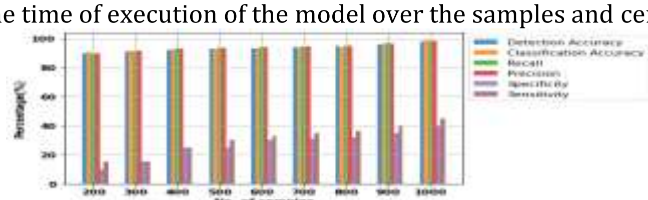

Fig. 8. Performance of the presented model with various metrics

The work of suggested model on various measures is depicted in Figure 8. At 200 samples the system at first gave the system the following. has decent performance measures. Detection accurate, classification accurate, recall, precise, specific, and sensitivity all are promising, though with room to. enhancement. But, with increasing sample size, the tendency towards any sample size is to decrease. 1000, there is a significant performance enhancement in the board. Recall, precision, detection and classification accuracy, specificity, and sensitivity greatly enhance, displaying the increased effectiveness of the system. Notably, detection and classification accuracy method 98%, and recall, precision, specificity and sensitivity also exhibit significant levels of. improvements, to the point of 98.5% or higher in a few instances. The tendency towards an increase in these metrics as the increase in takes place. sample size implies that there is a direct correlation between increased performance. associated with the access to additional information. This underscores the value of data richness in optimization of system features. and performing better in different spheres.

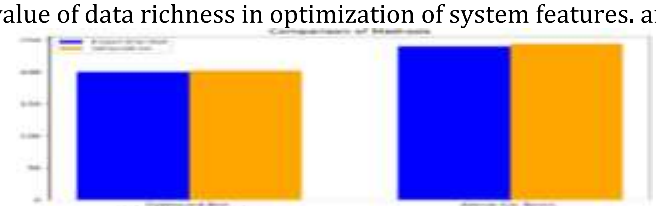

Fig. 9. Experimental validation of the proposed system

Figure 9 displays the experimental validation of the suggested system. Here, the suggested system is contrasted with two additional mathematical models: the Kernel Cat Boost Tree and the Optimized Bee Vector Markov Modulation. It is evident from the data that the simulation produced somewhat better outcomes than the experiment, and the model's ideal settings may be the cause. Nonetheless, the usefulness of the suggested system is demonstrated by the Optimized Bee Vector Markov Modulation approach, which performs well for the simulation and testing findings. This validates the use of the suggested approach to enhance the multilevel inverter system's real-time fault detection and categorization.

D. Comparison Results

This section will compare the proposed method's classification accuracy with a number of current techniques, such as the SVM (Support Vector Machine), LSTM (Long Short-Term Memory), BP (Backpropagation), and CWT-DCNN (Continuous Wavelet Transform-Deep Convolutional Neural Network). Additionally, a number of other traditional machine learning techniques, such as the Decision Tree (DT) and KNN (k-Nearest Neighbors) methods, will be compared. As stated in the earlier studies [26–27], a number of performance indicators, such as precision, recall, F1 score, and specificity, will be used to assess the performance.

Thus, with the comprehensive analysis, the proposed method is able to prove the effectiveness of the performance compared to the existing techniques used for the detection and classification of the faults that may occur in the multilevel inverter systems. In addition, the performance is compared based on the execution time and the efficiency of the training process. Thus, the proposed method is able to mitigate the interference that may occur.

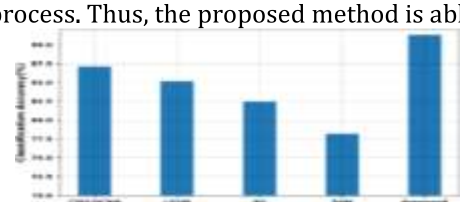

Fig. 10. Comparison of classification accuracy

The classification accuracy comparison between the suggested strategy and other current methods is shown in Figure 10. The proposed method's classification accuracy is contrasted with that of other methods, including CWT-DCNN, LSTM, BP, and SVM. While the classification accuracy of CWT-DCNN, LSTM, BP, and SVM is 87.11%, 85.16%, 82.44%, and 78.2%, respectively, the suggested model obtains a classification accuracy of 91.3%. Fault detection is improved because to Optimized Bee Vector Markov Modulation.

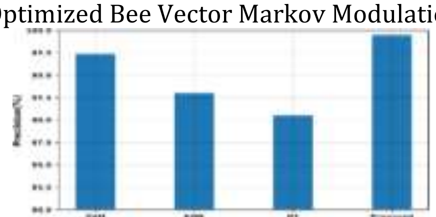

Fig. 11. Comparison of Precision

The comparative analysis of precision has been carried out in Figure 11. The presented method's Precision is contrasted with that of other methods now in use, including SVM, KNN, DT. The Precision of the proposed model is 99.5%, whereas the Precision of the SVM, KNN and DT are, respectively, 97.4%, 93.02%, 90.51%. The fault detection has improved with the use of the Optimized Bee Vector Markov Modulation.

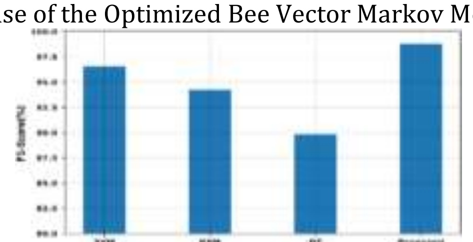

Fig. 12. Comparison of F1-score

Figure 12 compares the F1-score of the presented model with various existing techniques. The F1-score of the proposed is compared with existing methods such as SVM, KNN, DT. F1-scores of the SVM, KNN, DT are 96.57%, 94.26%, 89.82%, respectively, whereas the F1-score of the suggested model is 98.8%. The application of the Kernel Cat Boost Tree Vector Event has increased the multi-level inverters' classification accuracy.

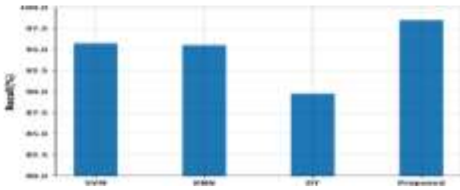

Fig. 13. Comparison of recall

The presented model's recall is compared with different approaches in Figure 13. The proposed recall is contrasted with many other approaches like SVM, KNN, and DT. The proposed method has a recall of 98.5%, whereas the SVM, KNN, and DT have a recall of 95.74%, 95.54%, 89.78%, respectively. The recall has risen with the use of the Optimized Bee Vector Markov Modulation.

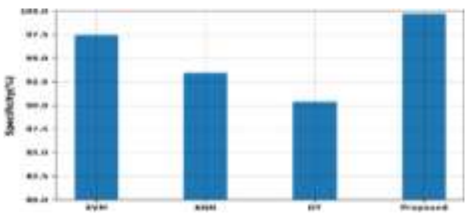

Fig. 14. Comparison of specificity

Figure 14 compares the specificity of the defined model with alternative methods. The specificity of the defined method is compared with several other methods, like SVM, KNN and DT. The SVM, KNN and DT have a specificity of 97.44%, 93.44%, 90.37%, respectively, whereas the proposed method has a specificity of 99.7%. Applying the Kernel Vector Principal Machine method strengthens fault detection capability.

TABLE 1: COMPARISON OF PARAMETERS WITH EXISTING TECHNIQUES

Parameters	CWTDCNN	LSTM	BP	SVM	Proposed
Classification accuracy	87.11%	85.16%	82.44%	78.2%	91.3%

TABLE 2: COMPARISON OF PARAMETERS WITH EXISTING TECHNIQUES

Parameters	SVM	KNN	DT	Proposed
Precision (%)	97.40	93.02	90.51	99.5
Recall (%)	95.74	95.54	89.78	98.5
F1-Score (%)	96.57	89.78	89.82	98.8
Specificity (%)	97.44	98.5	90.37	99.7

TABLE 3: TECHNIQUE USED

Parameters	Technique Used
Precision	Optimized Bee Vector Markov Modulation
Recall	Optimized Bee Vector Markov Modulation
F1-score	Kernel Cat Boost Tree Vector Event
Classification accuracy	Optimized Bee Vector Markov Modulation
Specificity	Kernel Vector Principal Machine Approach

However, it should be stated that the comparison of the suggested method with the previously discussed approaches further supports the method's efficacy in identifying flaws in multilayer inverters. The suggested approach is the best of the previously discussed approaches. With a precision of 99.55%, a recall of 98.5%, and an F1-score of 98.8%, this clearly demonstrates the genius of the suggested approach. Moreover, the proposed technique boasts a tremendous classification accuracy of 91.3%. This, indeed, speaks volumes for the proposed technique being a better technique for the detection of faults in multilevel inverters. This supremacy of the proposed technique over other techniques, such as the CWT-DCNN, LSTM, BP, and SVM techniques, is more pronounced.

V. CONCLUSION

The multi-level inverters are a power electronic switch that finds application in power conversion in various renewable energy groups, electric motor drives, and other applications. The limitations of this study are that it requires extremely large hardware resources and knowledge to execute the fault detection algorithms, the system is extremely sensitive to the tuning and optimization of the parameters, and it cannot be scaled to larger multilevel inverter structures. Its design, which is tactically preoccupied with reducing the EMI frequencies, is a necessary innovation that greatly inspired the accuracy in fault signal detection. Moreover, the Kernel Cat Boost Tree Vector Event continues to be incorporated, which adds to the accuracy in fault classification, providing an exhaustive survey of the peculiarities of the nonlinear interaction of faults. The comparative analysis represents an unqualified example of the power of the method with the best performance metrics, i.e., 91.3% accuracy of classification, an incredible 98.8% of F1-score, 99.7% of specificity, and 99.5% of precision. when compared to other methods such as CWT-DCNN, LSTM, BP, SVM, KNN, and DT. Such a complete structure not only ensures the sensitive performance of the method's operation but also offers a good opportunity to those representing it to have a considerable rate of error detection much higher in real conditions. This represents an important step forward towards advancing the technology related to multilevel inverters, normally the promise of which includes fault detection.

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