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A Hybrid Deep Learning-Based (HYDRA) Framework for Multifault Diagnosis Using Sparse MDT Reports

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ABSTRACT Diminishing viability of manual fault diagnosis in the increasingly complex emerging cellular network has motivated research towards artificial intelligence (AI)-based fault diagnosis using the minimization of drive test (MDT) reports. However, existing AI solutions in the literature remain limited to either diagnosis of faults in a single base station only or the diagnosis of a single fault in a multiple BS scenario. Moreover, lack of robustness to MDT reports spatial sparsity renders these solutions unsuitable for practical deployment. To address this problem, in this paper we present a novel framework named Hybrid Deep Learning-based Root Cause Analysis (HYDRA) that uses a hybrid of convolutional neural networks, extreme gradient boosting, and the MDT data enrichment techniques to diagnose multiple faults in a multiple base station network. Performance evaluation under realistic and extreme settings shows that HYDRA yields an accuracy of 93% and compared to the state-of-the-art fault diagnosis solutions, HYDRA is far more robust to MDT report sparsity.

INDEX TERMS Root cause analysis, cellular data sparsity, data enrichment, multi-fault diagnosis, minimization of drive tests, hybrid deep learning, radio environment maps, image inpainting, self healing, network automation.

I. INTRODUCTION

Management tasks in emerging cellular networks are becoming more complex due to evolving network architecture, rapidly increasing and diversifying network traffic, and the growing number of network parameters [1], [2]. Among several management challenges in emerging cellular networks, one major challenge is the timely detection and diagnosis of faults. The increasing complexity of emerging cellular networks and the ultra-reliability requirements of numerous emerging applications are intensifying the challenges of the detection and diagnosis of faults.

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Faults, that can lead to hard outages (complete coverage degradation) or soft outages (partial service degradation) in cellular networks can occur due to several reasons. These include poor network design, including improperly configured parameters such as the number, types, and locations of the base stations (BS), antenna heights, sector orientation, tilt, power, frequency reuse patterns, or the number of carriers, among others. Other types of faults can occur due to hardware, software, or functionality failures (e.g., power supply or radio board and network connectivity failures) [3].

Traditionally, outages resulting from faults are detected by human-based monitoring of either alarms, performance counters, or complaints filed by network subscribers [3], [4].

This can take hours and at times days to resolve outage issues. Therefore, for better Quality of Experience (QoE) and Quality of Service (QoS), network providers spend a lot of money, time, and resources to do coverage testing via drive tests. This helps them resolve problems caused by poor parameter configuration and environment change at the cost of heavy capital and operational expenditures. Outages caused by parameter misconfiguration or hardware or software failure that did not raise an alarm are even more challenging to detect and diagnose. These require network experts to manually analyze network logs which can, in turn, further slowdown the outage compensation process. Moreover, this challenge of fault detection and root cause analysis is especially aggravated in emerging ultra-dense networks, where the same advances in network design that bring advantages such as higher data rates and capacity as compared to legacy networks, e.g., densification, also lead to the growing complexity of the network, making it difficult to manually detect and diagnose faults. The additional burden of growing operational and capital expenditures is making matters worse.

Therefore, outage detection and fault diagnosis through the conventional human monitoring of logs and counters or manual collection of data through the drive-test is neither a practical nor viable option particularly in emerging complex and dynamic network environments [5], [6].

Network automation solutions, i.e., self-healing solutions are needed to automate the process of fault detection and diagnosis. Only when the outages and their root cause are detected promptly without drive tests and humans in the loop, will the network be able to take actions to compensate for these outages autonomously. The automatic root cause analysis of outage problems can save billions of dollars to network providers annually, by replacing manual resolution of coverage-related anomalies [4]. To wake of this need, the 3GPP has introduced minimization of drive test (MDT) reports feature [7], where the user equipment (UE) periodically sends network coverage related key performance indicators (such as Reference Signal Received Power and Quality, RSRP, and RSRQ respectively) along with their geographical location to their serving base stations, thus eliminating the need for drive tests. Following the standardization of MDT reports, the problem of outage detection and automated fault diagnosis using MDT reports has gained significant attention in the literature.

The rest of the paper is organized as follows: The related work is presented in Section II. The considered network topology and data acquisition method are presented in Section III. The proposed HYDRA framework is described in section IV, details of proposed MDT data enrichment methods are presented in section IV-A, while a detailed implementation and intuition behind using a hybrid model for root cause analysis are explained in Section IV-B. Results and insights from the performance analysis are provided in section V and Section VI concludes this study.

II. RELATED WORK

Although outage detection has been studied extensively in the literature [8]–[14], relatively a small number of studies have focused on outage diagnosis [15]–[17].

Among the several studies that focus on outage detection, are works that use convolutional neural networks (CNN) [8], deep neural networks (DNN) [10], support vector machine (SVM) [12], and several other machine learning (ML)-based methods [10], [12], [18]–[21]. For a thorough review of outage detection, the reader is referred to a recent survey presented in [2]. A key insight from the extensive review presented in [2] is that almost all existing studies on outage detection and diagnosis overlook a major practical challenge while using MDT reports i.e., the spatial sparsity of MDT reports in the real network. That is most studies assume that MDT reports are available from each point in the area under concern, an assumption that does not hold in a real deployment. This is because MDT reports can be received only from bins where users are present. This usually is a small fraction of the area of interest. In ultra-dense deployments, small cells contain even fewer users compared to macro cells. This makes the number of MDT reports per cell even smaller. This poses a major practical problem for automation solutions that leverage MDT data. However, this problem is often overlooked in the literature by assuming that ample MDT reports are available to represent network KPIs in the whole coverage area.

In comparison to outage detection, outage diagnosis that is the focus of this paper, remains relatively under investigated in the literature. The study in [15] is among those few works that focus on outage diagnosis using self-organizing maps (SOM). Another such study in [22] also present a fault diagnosis framework using SOM. However, the solutions presented in both [15] and [22] are semi-supervised and require input from experts for accurate labeling of the clusters (formed based on different fault classes). Apart from that the SOMs are not robust to varying distributions of data, which makes them nongeneralizable to use with real network MDT reports, due to the sparse nature of MDT data.

In [23] researchers propose an ensemble model (combining two or more classification techniques) for fault diagnosis, which use multiple classifiers that diagnose the current state of the network (normal or anomalous) based on a majority vote, from given network key performance indicators (KPIs) e.g., signal-to-interference-plus-noise ratio (SINR), received signal received power (RSRP), etc. This solution adds cost sensitivity based on misclassification of faults. The cost function assigns different costs for different faults depending upon the severity of the fault. However, the MDT training data sparsity and multi-fault in multiple BSs are not addressed in this work either.

The most relevant to this work are the studies presented in [24]–[26]. The researchers in [24] and [25] present a fault diagnosis solution using neuromorphic AI and classical ML methods, respectively. They use MDT reports to generate

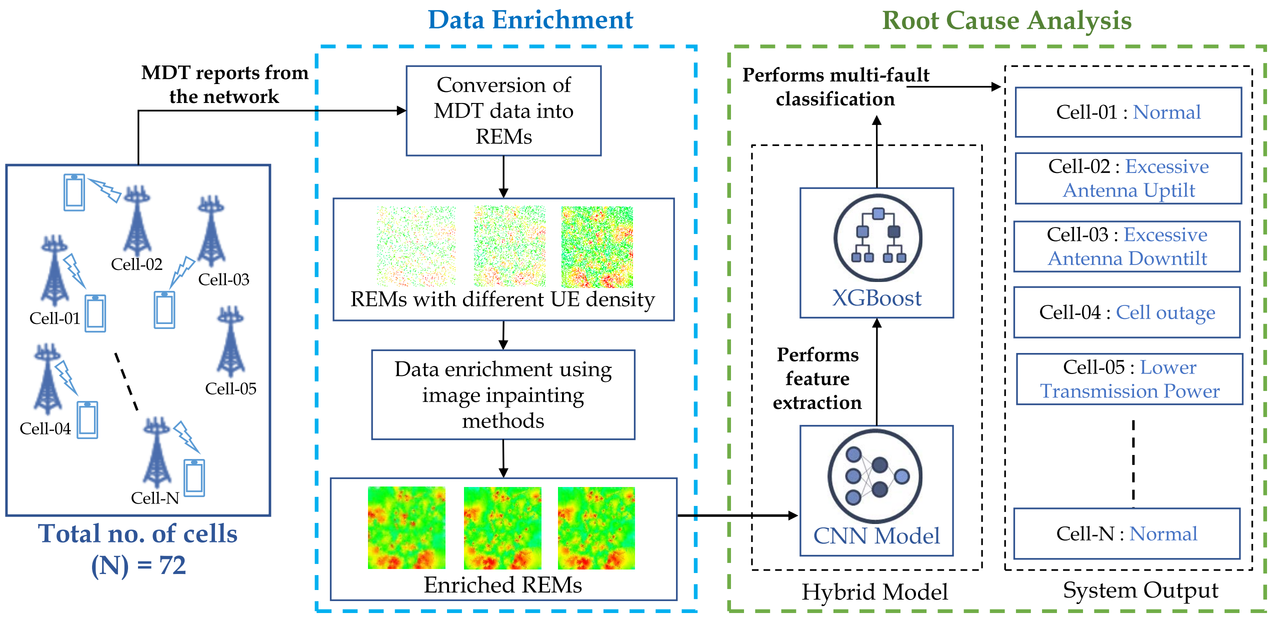


FIGURE 1. Proposed HYDRA framework for root-cause analysis of multi-fault in multiple BSs, based on image enrichment and hybrid deep learning.

radio environment maps (REMs). Their analysis shows that random forest (RF) outperforms CNN when MDT data is available from the entire coverage area. However, as explained earlier real network MDT data is expected to be both sparse and noisy. Also, both these studies consider faults in a single BS, i.e., they assume a single fault at a time. Hence, while offering a promising first set of results on fault diagnosis using only MDT data in a multi-BS network, the aforementioned assumptions in [24], [25] render these solutions unsuitable for real deployment. In [26] authors present a deep learning (DL)-based solution for the multi-fault diagnosis in one BS. But the proposed solution requires the drive-test to get the data of a key feature used in the model (throughput). The time and cost for the drive-tests makes this solution less scalable for practical deployment.

Based on the literature review summarized above there does not exist a practical fault diagnosis solution in the literature that has the following features.

1) **Capability to diagnose multiple faults in multi-base station deployment scenario.**
2) **Capability to operate with sparse/incomplete MDT reports.**

In order to address the above mentioned gaps in literature, we propose Hybrid Deep Learning-based Root Cause Analysis (HYDRA), which is the first solution that includes the capabilities identified above. HYDRA can detect multiple faults in multi-BS deployment scenarios with realistic sparse MDT data in fully automated fashion. To achieve these capabilities HYDRA has two key innovative components as illustrated in Fig. 1. The first component solves the MDT report sparsity problem by leveraging data enrichment techniques (explained in section IV-A). The second component consists of a novel hybrid of CNN and XGBoost based model to achieve reliable diagnosis despite noise and sparsity in the enriched or raw REMs.

A. CONTRIBUTIONS

The contributions of this paper can be summarized as follows

1) This paper presents first of its kind fault diagnosis solution that can reliably diagnose multiple faults in multiple BSs in the network, caused by both hard outages(network failures leading to no coverage) or soft outages (occurring due to inefficient configuration of network parameters) while using sparse MDT reports. In a real network, faults can occur in different BSs, and they can be of different types. HYDRA is robust to not only different kinds of faults and BS locations but also to variable user densities in the network. This makes HYDRA more feasible to implement in a real cellular network where user density and distribution, never remain static.
2) HYDRA is designed to work with realistic raw sparse MDT reports from the network. These reports are converted into REMs. The REMs are incomplete due to spatial sparsity of MDT reports resulting from varying user density. We present a practical solution to complete REMs. This is done by investigating and comparing state-of-the-art data enrichment techniques suitable for the problem. We perform multi-KPI comparative analysis of frequency selective reconstruction (FSR), Biharmonic Equations, and TELEA. Results show that FSR outperforms others and therefore is best suited for REM completion task in HYDRA.
3) The inherent noise in the REMs from sparsity of MDT reports and/or reconstruction makes task of fault diagnosis using REMs even more challenging.

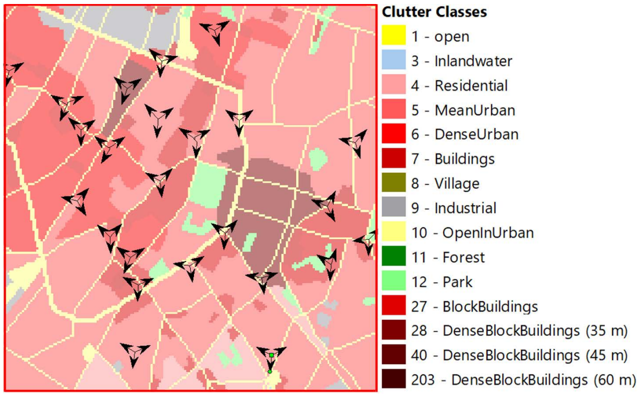


FIGURE 2. Network topology and geographical clutter information used in simulator for generation of synthetic MDT data.

This challenge is by passed in the literature by often assuming availability of complete and noise free REMs. Therefore, classic models such as SVM [12], RF [24], [25] and CNN [8] are often used and observed to yield adequate performance in the literature. Our analysis shows that these classic models do not attain adequate performance when realistically sparse MDT data is used to generate REMs. We also address this issue of data sparsity/scarcity by proposing and evaluating a hybrid deep learning model where a CNN is first used to extract the features and the features are then fed into an XGboost model to diagnose network coverage anomalies using raw MDT reports. It is observed that the extensive performance evaluation (using several suitable performance metrics) with varying degree of MDT data sparsity shows that proposed hybrid model performs better than both the models when used standalone in terms of robustness to noise and variable UE density.

III. NETWORK TOPOLOGY AND DATA ACQUISITION

Figure 1 provides a holistic view of the HYDRA framework. The framework has three major blocks: The first block is acquisition of MDT reports from the network explained in this section. The second block is conversion of raw MDT reports into REMs and data enrichment using image inpainting, thoroughly explained in Section IV-A. The third block is hybrid deep learning based root cause analysis using sparse REMs data, rigorously described with rationale and implementation details in Section IV-B.

A. NETWORK TOPOLOGY

The root-cause analysis framework we consider is designed for a real network but due to the unavailability of real data, a realistic commercial RF planning and optimization tool, **Forsk Atoll** [27] is used to generate and collect MDT reports. The simulated network topology considers an area from Brussels City, Belgium as shown in Fig. 2. We consider 15 different clutter types based on environmental conditions and terrain profiles. Aster propagation (advanced ray-tracing) is used as a propagation model because of its ability to better capture the idiosyncrasies in the environment as compared to empirical propagation models. We use the same locations and configuration parameters of BS used by a real network provider for its deployment in Belgium. Table 1 reports these settings. Therefore, the obtained coverage data can be assumed to be a very close representation of the ground truth of the MDT reports in area used in the simulation. The area of simulation is 13.292 km^2 with 24 macrocell BSs (72 cells) to generate data with multiple fault classes in multiple BSs simultaneously.

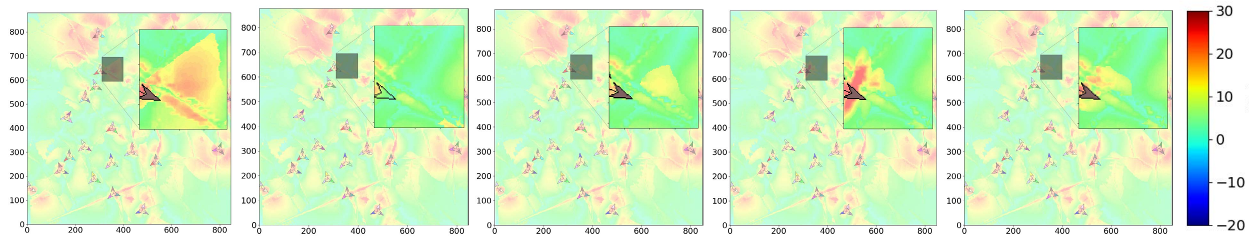
TABLE 1. Network scenario settings.

Network parameters	Values
Network layout	24 macro BSs (eNodeBs)
Sectors per BS	3 sectors/cells per BS
Carrier frequency	2100 MHz
Simulation area	13.292 km^2
Bin size	30m $\times$ 30m
Antenna height	Actual site heights
Propagation model	Aster propagation model (ray-tracing)
Clutter types	15 classes
Maximum transmission power	43 dBm
Cell individual offset (CIO)	0 dB
Antenna tilt	0^o
Antenna gain	18.3 dBi
Geographical information	Digital Terrain Model (ground heights) + Digital Land Use Map (clutter classes)

B. DATA ACQUISITION

We acquire MDT reports with 4 highly used fault classes in the literature for root cause analysis and self-healing frameworks: cell outage, low transmission power, excessive antenna uptilt, and excessive antenna downtilt [15], [28]. Figure 3 presents a visualization using SINR maps of different fault classes when induced on a selected cell in the designed network in the simulator. Fig. 3(a) represents a normal coverage scenario and the impact of other fault classes on cell coverage is illustrated in Fig. 3(b-e). The parameter configuration of the 4 fault classes is described as follows:

1) **Cell Outage (CO):** To simulate cell outage, we deactivate the transmitter on a selected site in the simulator. This simulates a no-coverage fault scenario around that cell. Figure 3(b) is presenting the CO scenario for highlighted cell.
2) **Low Transmission Power (LTP):** The maximum transmission power is 43 dBm for a normal BS in our designed network based on recommended value by [7]. We simulate the LTP fault scenario by reducing the maximum transmit power of a cell to 25 dBm (we select this value based on the industry experience of co-authors). Figure 3(c) shows an LTP scenario.



(a) Normal Coverage Map (b) Cell Outage (c) Low Transmit Power (d) Excessive UpTilt (e) Excessive DownTilt

FIGURE 3. REMs presenting different network conditions. (a) Normal, (b) cell outage, (c) low transmission power, this image is showing when transmission power drops to 25dBm, (d) excessive antenna uptilt, this is +20° tilt, and (e) excessive antenna downtilt, −20° tilt.

3) **Excessive Antenna Downtilt (EAD):** To induce excessive antenna downtilt we change the tilt value from 0° to 20°. Figure 3(d) present an EAD scenario.
4) **Excessive Antenna Uptilt (EAU):** Normal antenna tilt is 0°. We change the tilt value from 0° to −20°. Both antenna uptilt and downtilt values are selected based on co-authors' industry experience. The impact of EAU can be seen in 3(e) for a selected cell.

To ensure the practicality of the HYDRA, while generating simulated MDT reports, we randomly select four cells out of 72 cells in total and induce a random fault in them through a different independent random process. In this way, not only we can have different cells (based on location in the network) in each MDT report but also different types of fault (CO, LTP, EAD, or EAU). We have 19933 different MDT reports of the network, each having 4 anomalous and 68 normal cells and each anomalous cell with a different fault.

We then convert raw MDT reports into SINR REMs. The REMs built from MDT reports are expected to be sparse by varying degree depending on the user density, time interval used to aggregate MDT reports in a bin, and size of the bin [29]. We model this practical constraint by creating REMs with varying degree of sparsity as shown in Fig. 4. To overcome the errors in fault detection and diagnosis caused by the sparsity in REMs in this paper we leverage image inpainting to enrich the sparse REMs. To the best of our knowledge image inpainting is not used in cellular domain because there are just few published works, where MDT reports are used in the form of REMs. The available literature which considers REM-based outage diagnosis [24], [25], does not consider sparsity. This study is the first to investigate impact of data sparsity and provide a detailed performance comparison of state-of-the-art-image inpainting techniques to address the practical problem of sparsity in MDT data and REMs in Section IV-A.

IV. THE HYDRA FRAMEWORK FOR FAULT DIAGNOSIS USING SPARSE MDT DATA

In this section we present intuition and implementation details of block II (data enrichment) and block III (root cause analysis) of HYDRA framework explained in Figure 1.

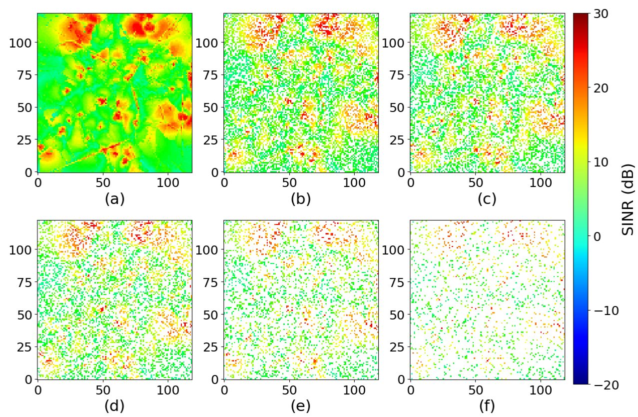


FIGURE 4. REMs with various MDT report densities (a) Complete REM (203 UEs/cell (1101 UEs per km^2)). (b) 100 UEs/cell (550 UEs per km^2). (c) 80 UEs/cell (440 UEs per km^2). (d) 60 UEs/cell (330 UEs per km^2). (e) 40 UEs/cell (220 UEs per km^2). (f) 20 UEs/cell (110 UEs per km^2).

A. DATA ENRICHMENT USING IMAGE INPAINTING

MDT reports in a real networks are expected to be sparse due to reasons such as low UE density [29]. There are various methods available to enrich sparse MDT data such as interpolation [30], regression clustering [31], and kriging [32]. While these methods work well for the enrichment of numerical data, our goal is to ultimately build REMs i.e., images. Therefore, instead of classical interpolation techniques image inpainting methods are more suited to our purpose here. Image inpainting methods based on fast marching methods [33], frequency selective reconstruction (FSR) [34], and Biharmonic equation provide a good balance between accuracy and time required to reconstruct a complete REM from a given sparse REM. Building on insights from these works, to address REM sparsity, we use image inpainting methods to enrich data before passing it on to root cause analysis block of Fig. 5. Through extensive survey of the state-of-the-art image inpainting techniques we select (based on accuracy and efficiency) following methods to recover missing SINR values in the REMs. A comparative analysis of these methods on a sparse dataset (100 MDT reports/call) in the cellular networks domain is given in Table 2.

1) **Frequency Selective Reconstruction (FSR):** FSR reconstructs missing SINR values using Fourier basis functions from available neighboring SINR values

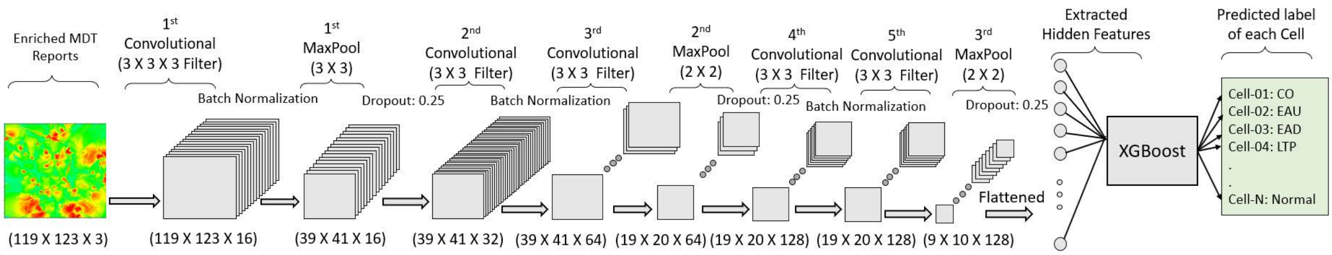


FIGURE 5. Proposed hybrid deep learning model. CNN extracts hidden features from REMs and XGBoost performs the classification operation.

TABLE 2. Performance evaluation of data enrichment methods.

Method	RMSE (dB)	SSIM (%)	PSNR (dB)
FSR	**8.6**	**90**	**22.81**
Biharmonic Equation	9.3	87	21.23
Navier-Stokes (NS)	9.45	86	20.8
TELEA	9.7	85	20.84

in the REM. This is a computationally expensive method but is highly parallelizable and with the use of GPUs can achieve significantly accurate results in considerably less time [34].

2) **Biharmonic Equations:** This method estimates the missing pixels using fourth-order partial differential equations. This is a computationally very expensive process due to the computation of multiple derivatives to estimate missing SINR values. It is quite accurate on small datasets but requires a lot of time to reconstruct bigger datasets.
3) **TELEA:** TELEA uses the principles of the fast marching method [33] to reconstruct missing SINR values in the REM using normalized weighted sum computed from known neighborhood SINR values.
4) **Navier-Stokes:** This method reconstructs the missing SINR values in the REM using the principle of heuristic based on fluid dynamic equation (Navier-Stokes) [35]. The reconstruction process starts on the edges and keeps on filling the missing SINR data towards the center of the REM.

To evaluate the performance of data enrichment methods we use root mean square error (RMSE), structural similarity index measure (SSIM), and peak signal to noise ratio (PSNR) as performance metrics. It is evident from Table 2 that FSR outperforms the rest of the inpainting methods. In this work RMSE is the most important metric because that represents the difference between estimated (inpainted) value of SINR against the ground truth.

B. ROOT CAUSE ANALYSIS BASED ON HYBRID DEEP LEARNING

In this section we elaborate the **root cause analysis** block in the HYDRA framework (right most block in Fig. 1). We also explain the intuition behind using a hybrid deep learning model, implementation, and performance metrics to compare the proposed model against the widely used techniques for root cause analysis.

- **Why a hybrid deep learning model?** The rationale behind using a hybrid model stems mainly from the fact that in the cellular networks, the availability of training data is still a challenge even in the age of big data [29]. For this reason, we cannot use CNN alone as it requires large training data and is computationally more expensive as compared to classical ML models. On the other hand, classical ML methods when used alone are less robust to noisy data (noise is induced due to the application of image inpainting to enrich sparse MDT data) as compared to CNN. To overcome this challenge, we use a hybrid approach where we use CNN for hidden feature extraction from REMs to take advantage of the robustness it offers towards noisy images [36], [37]. Then we pass the extracted features to XGBoost which is computationally efficient as compared to the classification layer of CNN [38] and provides better accuracy when used as a hybrid [39], [40]. XGBoost takes the extracted features and performs fault diagnosis. Figure 5 provides a detailed elaboration of the proposed hybrid model.
- **Minimization of drive test reports:** MDT reports are introduced by 3GPP in release 10, these reports have several features e.g. user location and network quality of service based on certain KPIs like RSRP, RSRQ, and SINR to name a few [7]. In this research we use SINR one of the available KPIs in MDT reports. The major advantages that MDT reports offer are reduction of human intervention, reduction in operational expenditure as well as reduction in time-inefficiency arising from offline configurations required for coverage related faults detection and diagnosis. These features make MDT reports a key enabler for ML-based self-organization envisioned for emerging cellular networks.
- **Convolutional neural network:** A CNN is a class of neural networks that specializes in processing data that has a grid-like topology, such as an image. CNN uses a dynamic kernel, and convolutional layers instead of fully connected layers, which reduces the number of weights in each layer and hence requires less computation time, that makes CNN computationally more efficient. We used CNN for feature extraction from REMs that

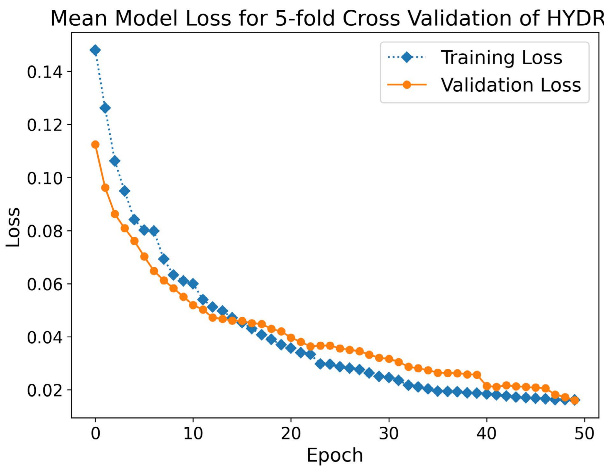


FIGURE 6. Mean model loss for 5-fold cross validated HYDRA.

are image representation of network coverage maps. The CNN architecture in Figure 5 is our top-performing model. The loss vs. epoch graph of this model is present in Figure 6, this graph is based on mean loss values of 5-fold cross validation for 50 epochs. This graph shows the lack of overfitting as well as underfitting in the model training process as the gap between training and validation loss converges after 50 epochs. A detailed explanation of each feature extraction function is given as follows:

1) Convolution: convolution extracts important hidden features e.g. boundary edges from the input coverage map. In this study boundaries are very important to distinguish between coverage regions of different sites. The dimensions of output matrix of convolution operation are defined as Equation 1 and 2.

$$O_r = \frac{(I_r - F + 2P)}{S} + 1 \quad (1)$$

$$O_c = \frac{(I_c - F + 2P)}{S} + 1 \quad (2)$$

where O_r, O_c, I_r and I_c represents the number of rows and columns of the output and input matrix respectively, while F, P and S represents the size of kernel, padding and length of the stride.

2) Batch Normalization: To accelerate the learning of CNN and to address internal covariate shift, batch normalization is used [41]. This transformation normalizes the input to a layer by maintaining the mean and standard deviation close to 1 and 0 respectively.

3) Pooling: Pooling is used for down-sampling of feature matrix which reduces its sensitivity and makes the feature extraction process robust to changes. We use max pooling to ensure the presence of the most activated features.

- **Extreme gradient boosting:** XGBoost is a decision-tree-based ensemble ML algorithm that uses a gradient boosting framework [42]. The tree-based nature and gradient boosting makes XGBoost yield superior results using fewer computing resources in the shortest amount of time. Time and computation efficiency is the reason we use XGBoost as a classification model of HYDRA instead of other ML models like artificial neural networks (ANN) [38], RNN, MLP, or extreme learning machines (ELM) [39], [40]. Furthermore, it gives more accurate results as compared to SVM and random forest. A detailed performance analysis of XGBoost against SVM and random forest is present in Section V.
- **Performance metrics:** As we propose a solution for a multi-label multi-class problem, unlike a simple classification problem, it requires special performance measuring metrics [43], [44], due to the biased nature of data towards normal class. Hence, we choose following performance metrics to evaluate the HYDRA.

1) **F1-Score (F1):** F1-score combines both precision and recall in one metric by taking their harmonic mean. This provides a more realistic performance analysis because it minimizes the chance of bias towards the majority class in the data. F1-score of a class is defined by 3

$$F_1 = \frac{Tp}{Tp + \frac{1}{2}(Fp + Fn)} \quad (3)$$

where Tp is true positive (%), Fp is false positive (%), and Fn is false negative (%) of the respective class.

2) **Exact Match Ratio/Subset Accuracy (EMR):** According to EMR, a diagnosis made by the model will be correct only if the network condition of all the cells in the network are diagnosed correctly. In this study we have a network designed with 72 cells, even if the network condition of 1 out of 72 cells for a given REM is predicted incorrectly, that REM will be considered as an incorrect prediction. This is considered a very strict performance metric, but to present a critical performance analysis we include it in our results. EMR is defined by Equation 4.

$$EMR = \frac{1}{N} \sum_{i=1}^{N} I(P_i = T_i) \quad (4)$$

where I is a proposition function which returns 1 if all 72 cells are correctly diagnosed else returns 0.

3) **Proportionally Correct Diagnosis (PCD):** We present a worst-case performance analysis of HYDRA using PCD, because even if it diagnose 2 out of 4 faults correctly that can help compensate half of the anomalous cells in the network. So, besides EMR we present proportionally correct results. PCD presents percentage of cases when 4, 3, 2 or 1 faults (out of 4) are correctly diagnosed from a given REM.

TABLE 3. F-score comparison of ML algorithms for different network conditions on sparse training and testing data (100 MDT reports/cell).

Network Condition	Machine Learning Algorithm									
	Support Vector Machine		Random Forest		XGBoost		CNN		HYDRA	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Cell Outage	0.852	0.841	0.851	0.84	0.856	0.847	0.86	0.846	0.91	**0.905**
Low Transmit Power	0.85	0.841	0.856	0.85	0.84	0.863	0.867	0.865	0.915	**0.902**
Excessive Antenna Downtilt	0.885	0.871	0.854	0.869	0.875	0.872	0.88	0.874	0.94	**0.939**
Excessive Antenna Uptilt	0.881	0.873	0.868	0.864	0.877	0.867	0.874	0.866	0.924	**0.921**

TABLE 4. F-score comparison of ML algorithms for different network conditions on enriched (using FSR image inpainting) training and testing data.

Network Condition	Machine Learning Algorithm									
	Support Vector Machine		Random Forest		XGBoost		CNN		HYDRA	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Cell Outage	0.847	0.843	0.852	0.842	0.858	0.852	0.863	0.850	0.91	**0.920**
Low Transmit Power	0.859	0.862	0.866	0.860	0.91	0.905	0.917	0.907	0.915	**0.914**
Excessive Antenna Downtilt	0.895	0.893	0.904	0.896	0.915	0.910	0.923	0.911	0.99	**0.989**
Excessive Antenna Uptilt	0.871	0.897	0.918	0.904	0.917	0.920	0.927	0.922	0.989	**0.981**

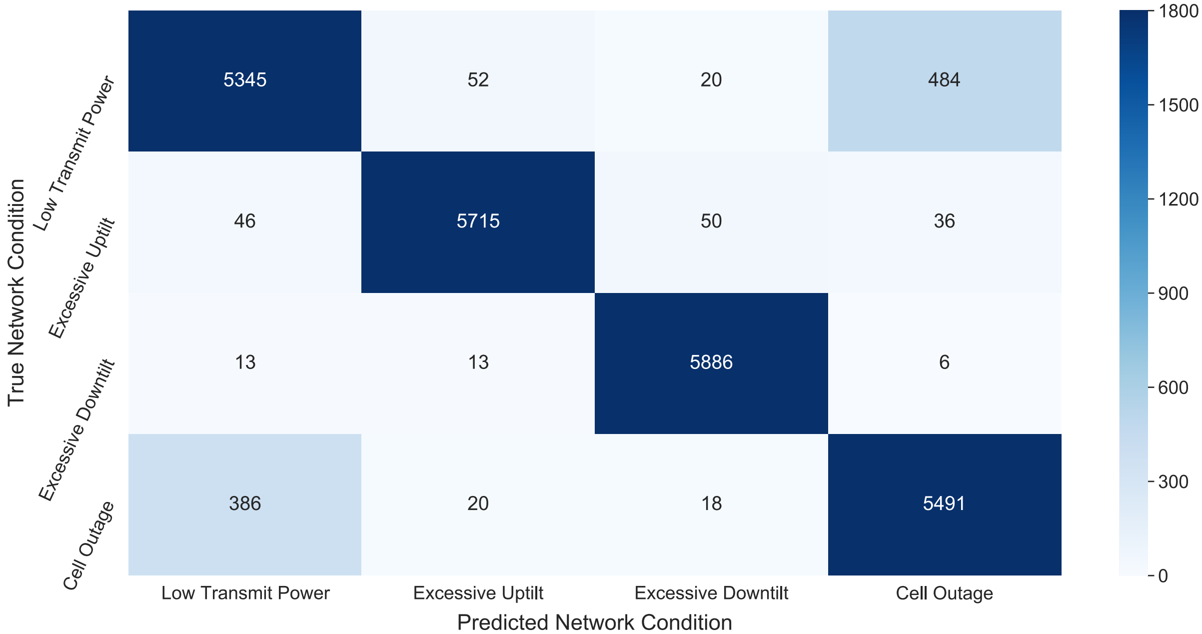
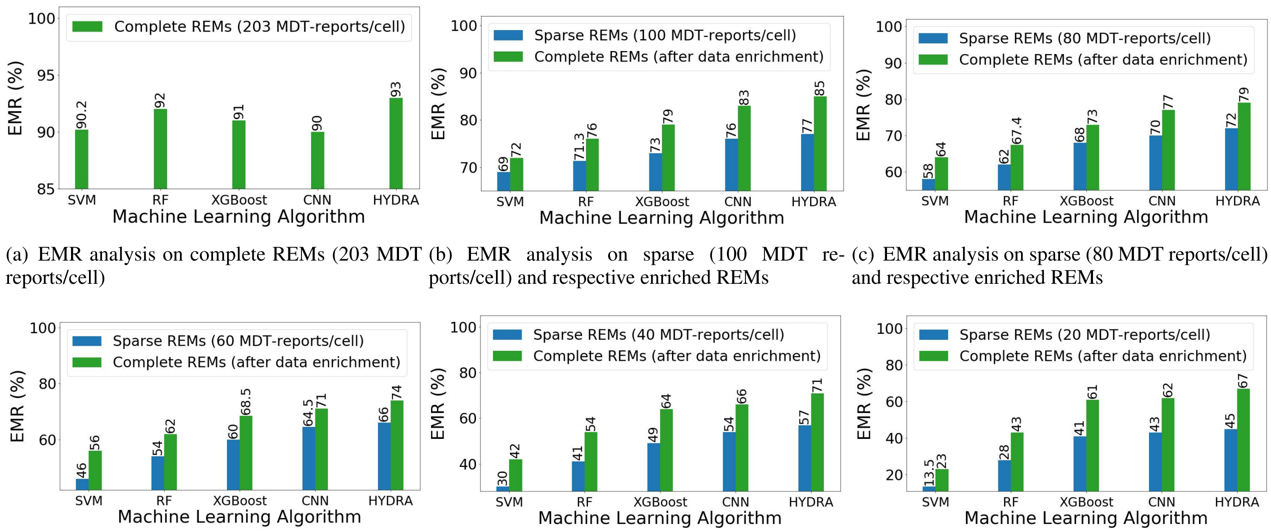


FIGURE 7. Mean confusion matrix for multi-fault diagnosis for HYDRA using 5-fold cross validation.

V. RESULTS AND COMPARATIVE ANALYSIS

We used 5-fold cross validation method [45] for the performance analysis presented in this section. Because cross validation ensures that each sample from the original dataset has an equal chance of appearing in training and validation set. Which is well suited approach when we have limited input data. We compare the performance of HYDRA against the state-of-the-art ML methods used for detection and diagnosis of outages in the literature. These include SVM [12], [46], [47], RF [24], [25], standalone XGBoost and standalone CNN [24]. We evaluate HYDRA with different UE densities to analyze its efficacy in realistic settings (i.e., robustness to sparsity of MDT reports in a cell/area). Figure 8 presents performance evaluation of state-of-the-art ML/DL



(a) EMR analysis on complete REMs (203 MDT reports/cell)

(b) EMR analysis on sparse (100 MDT reports/cell) and respective enriched REMs

(c) EMR analysis on sparse (80 MDT reports/cell) and respective enriched REMs

(d) EMR analysis on sparse (60 MDT reports/cell) and respective enriched REMs

(e) EMR analysis on sparse (40 MDT reports/cell) and respective enriched REMs

(f) EMR analysis on sparse (20 MDT reports/cell) and respective enriched REMs

FIGURE 8. EMR based performance analysis on sparse and respective enriched REMs. Note: (REMs with 203 MDT reports per cell are full coverage maps, so do not require enrichment).

models for sparse data (considering various UE densities) and enriched data (enhanced using FSR image inpainting as explained in Section IV-A). Figures 8(b) - 8(f) provide a comparative analysis of sparse and enriched data using EMR as metric. The insights coming from performance analysis of selected models on sparse and enriched data can be summarized as follows:

1) **Performance for each fault class based on F-1 score:** Table 3 presents a comparison of HYDRA based on F-1 score for each fault class against SVM, random forest, XGBoost, and standalone CNN on sparse data. This can be seen that HYDRA outperforms other methods based on F-1 score with a consistent F-1 score of above 0.90 for each network fault. Table 4 provides fault diagnosis results on enriched data. A significant improvement in F-1 score can be seen for both antenna uptilt and antenna downtilt but there is relatively less improvement for cell outage and low transmit power, on enriched data. The reason for no improvement in cell outage and low transmit power is because cell going through complete or partial outage will not have much coverage even after the data enrichment process, so the diagnosis accuracy remains almost the same.
2) **Performance analysis based on confusion matrix:** Figure 7 present thorough insights about performance of HYDRA for each network fault. Two network conditions that are not well distinguished are lower transmit power and cell outage, both the faults are confused by HYDRA as one another. That makes sense if we look at Fig. 3(b) and Fig. 3(c) cell outage and low transmit power affect the coverage of a cell in a similar fashion. Therefore, it is relatively more challenging to distinguish between cell outage and low transmit power as compared to excessive antenna uptilt and downtilt. Resolving the high-rate of confusion between these two specific faults i.e. low transmission power and cell outage for other reasons, can be an interesting topic for a dedicated future study as it may have to leverage Bayesian analysis and historical fault logs to establish priors
3) **Performance on sparse REMs:** From Fig. 8(a), we can observe that SVM and RF perform slightly better than CNN and XGBoost on complete REMs (i.e., when the number of users is large enough to send MDT report from each bin of the area under consideration). This justifies the popularity of SVM for self-healing in the literature [12]. But a drastic drop in diagnosis performance can be seen for SVM and RF on sparse data. i.e., EMR drops from 90.2% to 69% and from 92% to 71.3% respectively, as the density of MDT reports drop from 203 in Fig. 8(a) to 100 per cell in Fig. 8(b). The downward trend in performance continues as the number of reports decreases per cell. EMR of SVM drops to 13.5% when MDT reports per cell decrease to 20 in Fig. 8(f). In contrast, the results show that HYDRA is relatively robust to the REMs sparsity and can diagnose faults with an EMR of 45%, even when REMs are extremely sparse with just 20 MDT reports/cell.
4) **Performance on enriched REMs:** From Fig. 8(f) HYDRA shows a promising improvement on enriched data as compared to sparse data. Figure 8(f), shows that HYDRA can diagnose faults with an EMR of 67% on data enriched from highly sparse (20 MDT reports/cell) REMs. This is a 22% improvement in EMR achieved using data enrichment and hybrid deep learning based diagnosis proposed in HYDRA.

TABLE 5. Performance analysis showing performance of ML algorithms for correctly diagnosing a proportion of faults.

		Machine Learning Algorithm				
Percentage of Instances with Correctly Diagnosed Faults	**MDT reports per Cell**	*Support Vector Machine*	*Random Forest*	*XGBoost*	*CNN*	*HYDRA*
1 out of 4 faults correctly diagnosed	203	100	100	100	100	**100**
	100	99	99.6	99.9	99.9	**100**
	80	94.5	97.9	99.7	99.8	**100**
	60	91.5	95.3	99.4	99.5	**99.9**
	40	86	94.9	98.2	98.5	**99.8**
	20	74	80	88	90.3	**99.2**
2 out of 4 faults correctly diagnosed	203	99.5	99.9	99.9	99.9	**100**
	100	98.2	99	99.4	99.6	**99.8**
	80	91	97	97.2	98.2	**99**
	60	86	89.2	94.2	95	**97**
	40	77	79	89	91	**93**
	20	68	71	82	84	**89**
3 out of 4 faults correctly diagnosed	203	97.5	97.9	98	98.5	**99.8**
	100	82	88.5	92	93	**96**
	80	75	85	87.2	88	**92**
	60	62	71	82	83	**87**
	40	48	64	76.9	78	**81**
	20	37	49	71	72	**76**
4 out of 4 faults correctly diagnosed	203	90.6	93	93	93.5	**95**
	100	72	77	84	84.5	**86**
	80	68	69	74.7	77	**79**
	60	56	62	69	72	**75**
	40	44	56	65	66	**71.8**
	20	25	43	62	63	**68**

5) **Proportionally correct diagnosed faults on enriched data:** Furthermore, a worst-case performance analysis is presented in Table 5, showing the proportion of correctly diagnosed faults using different MDT report densities. It can be seen from Table 5 that HYDRA can correctly diagnose at least 2 faults in the network with 100% accuracy for complete REMs and with 89% accuracy from highly sparse (20 MDT reports/cell) MDT data. Furthermore, the proposed model can reliably diagnose 3 of the 4 faults 76% of the time from highly sparse MDT data. And it can identify at least one fault in around 99% of the maps enriched from just 20 MDT reports/cell sparse data.

VI. CONCLUSION AND FUTURE WORK

This paper presents a novel and practically usable framework for root cause analysis of coverage-related anomalies in emerging cellular networks, named HYDRA. The practicality of HYDRA stems from its ability to diagnose faults even from very sparse minimization of drive tests (MDT) data, a capability that no state-of-the-art outage detection or fault diagnosis solutions offer. The MDT data sparsity issue is addressed in HYDRA through data enrichment via image inpainting methods. The sparsity itself and then the inpainting methods add noise to the resultant REM, which makes diagnosis harder. To overcome this problem, HYDRA leverages a hybrid model that combines CNN and XGBoost, where former performs feature extraction for MDT-based REMs and later uses the extracted features to perform fault diagnosis. This hybrid model give HYDRA the robustness against the noise. We evaluate HYDRA in realistic deployment with 24 macro base stations (BSs) where multiple faults in multiple BSs are induced simultaneously. We test HYDRA performance against varying level of MDT data sparsity i.e., user densities and compare it with state-of-the-art ML based approaches for fault diagnosis. Results show that while HYDRA can diagnose faults with same accuracy (93%) as the state-of-the-art algorithms when impractical assumption of full MDT based coverage map is made, in practical scenario of sparse MDT reports (e.g. only 20 MDT reports/cell) HYDRA gives (67-45) 22% improved performance yielded by the image enrichment component for data enrichment and hybrid deep learning based model for fault diagnosis.

For the future research, there are multiple directions that can be investigated. One interesting direction with practical impact would be investigation of techniques that can delineate the two faults that show high confusion rate i.e., low Tx power and cell outage. This can be done by leveraging Bayesian or other conditional classifiers that can account for priors by analyzing previous fault history. Inclusion of more coverage anomalies e.g., cell individual offset (CIO) etc., exploration of different KPIs e.g., RSRP, that can help improved diagnosis in the presence of more faults, and investigation of problem specific ML and data enrichment methods, are other few research directions among many others.

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For more details about the projects, please visit: https://www.ai4networks.com

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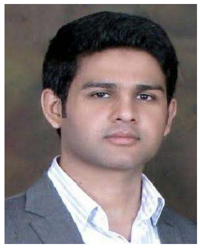

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