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Research Article

From Hexadecimal To Human-Readable: AI Enabled Enhancing Ethernet Log Interpretation And Visualization

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ABSTRACT

A term research paper presents a novel application of optimization and machine learning to networking with the following objectives: 1) converting binary data to human-readable form rather than the use of one of the existing network high-level packet analysis visualizations such as ethereal and shark or alternatives like hex editors, scripting languages, web servers for binary data. For UNIX/Linux OS, the Stack Glance tool from the Firewalls deployment suite can provide the needed result more smartly with high performance while doing much more work and saving time. With a high level of possibility, the Stack Glance visualizer supports filtering rulesets presented in text format and implements file feeding of log files. Popular DIY Feeding often used, as in our case, is the Robust Socket Chains (RSC) solution to provide horizontal scaling for the Stack Glance. RSC allows parallel execution consuming kind of build system with intelligent file partitioning or without partitioning. Releasing a new system, including IP rerouting for the parallel execution cost optimization based on the counting of logs reports, was done before the new packaging build.Vulnerabilities are typical to deep packet inspection devices. Such toolkits are usually intended neither to break anything before it's implemented in the real packet bypass or QoS field-specific implementation nor to build any infrastructure for the necessary results. A large amount of logs or a large enough number of instances for the same device should be harmful to using DPE/I for the network. Small logs and numerous UK small cyber-based businesses are still alive and growing. The solution was required: such a filtering solution, which is effective for high-capacity networks with low-capacity openings. Security event management systems do the job but not in a real-time, effective, and cost-efficient way. The value of results by false positive increasing became extremely high. Enhancements were introduced. The suggested solution is designed to boost these systems' implementation performance in case and network services in question are ready to solve about 700 VoIP issues.

Keywords: From Hexadecimal to Human-Readable, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM),Computer Science, Data Science,Vehicle, Vehicle Reliabilit

1. Introduction

Tools and techniques for network performance management and monitoring (NPM) use myriad data sources to achieve their goals, including but not limited to device configuration files (e.g., routers, switches), Simple Network Management Protocol (SNMP), NetFlow, Packet Sniffers, and Syslog. Instrumentation devices generate a massive number of very detailed logs that need to be collected, filtered, and distilled before analysis can occur. All network technology, operations, and development roles benefit from the availability of professional, but consumable, device logs (e.g., physical devices, administration settings, and a changelog). These professional logs effectively and efficiently capture errors, issues, change/activity history, performance, and environment.The physical-to-physical layer requirements of most human interactions with devices, whether they are directly connected to a KVM, cable modem/gateway, switches, printers, or servers, are satisfied by devices with data link layer adhering to standard IEEE 802.3 Ethernet specifications. The alluring aspect of historically aligning all of these data link layer interactions included within basic networking protocols was their inherently open, human-consumable, plain-English descriptions used to both describe and interface with the digital ports. Moreover, this historical characteristic is foundational for the manufacture of standard network management and monitoring tools.Recent scientific advances in machine learning and a growing interest in user and operator interfaces based on artificial intelligence (AI) highlight a significant and valuable opportunity to bring AI and hidden-shown data to the world of network device interaction logs. Specific employment and use of AI to interpret, visualize, and iteratively enhance user interfaces as well as pre-processing tools will drive network technology maturity. The development and long-term utilization of even marginally better AI-enhanced interpretive tools for non-transactional Ethernet header and emphasized data fields will improve and enhance growth, maintenance, and operation of all non-trivial 802.3 Ethernet data links into the future, particularly advancements in remote and edge computing, virtualization, network function virtualization, and local area network securityAs the complexity and scale of network environments continue to grow, the role of network performance management and monitoring (NPM) becomes increasingly critical. Tools and techniques employed in NPM utilize a diverse array of data sources such as device configuration files, SNMP, NetFlow, Packet Sniffers, and Syslog. These sources provide comprehensive insights into network operations, enabling professionals across network technology, operations, and development roles to effectively manage and optimize network performance.The abundance of detailed logs generated by instrumentation devices necessitates efficient collection, filtering, and distillation processes before meaningful analysis can be conducted. These logs capture a wide range of information including errors, issues, change history, performance metrics, and environmental conditions. By leveraging professional-grade logs, organizations can enhance troubleshooting capabilities, ensure regulatory compliance, and improve overall network reliability.The foundational nature of Ethernet specifications under IEEE 802.3 standards ensures compatibility and interoperability across a wide range of network devices and protocols. This historical adherence to open, human-consumable descriptions has been instrumental in the development of standard network management tools. However, recent advancements in machine learning present an opportunity to further revolutionize network management by integrating AI-driven interpretative and visualization tools.The application of AI can significantly enhance user interfaces and preprocessing tools by automating complex analysis tasks, visualizing data insights, and iteratively improving decision-making processes. This approach is poised to advance the maturity of network technologies, particularly in areas such as remote computing, edge computing, virtualization, network function virtualization (NFV), and local area network (LAN) security.Looking forward, the ongoing development and adoption of AI-enhanced tools promise to optimize the management, maintenance, and operation of Ethernet data links. By unlocking hidden patterns in data and enhancing interpretive capabilities, AI technologies will play a pivotal role in shaping the future landscape of network performance management and monitoring..

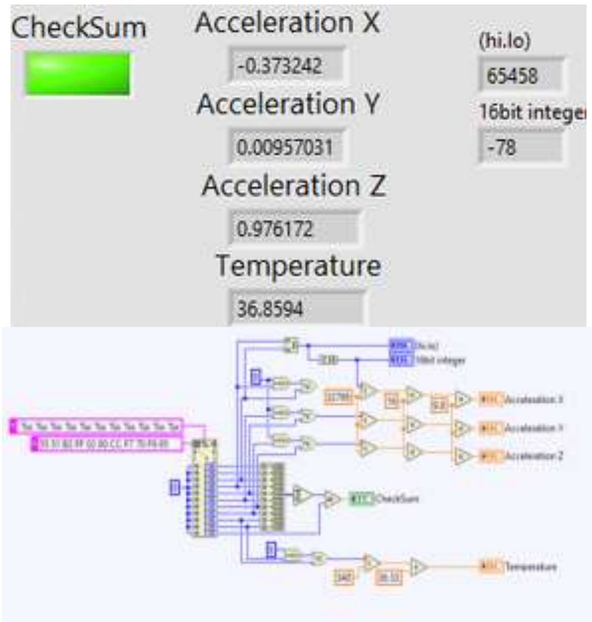

Fig 1:Converting Hexadecimal Data to a Physical Representation

2. Background and Significance

To support higher data throughput, the 56 Gb/s PAM4 Ethernet Enhanced Physical Layer offers a simplified, lightweight data link layer LDPC Encoded Scrambled with RS(528, 514) FEC layer, sending 514 payload bytes using 2x26.5625 Gb/s with 4xPAM4 modulation through a lossy multi-segment wired backplane or passive optical system. Using a fast DSP for optimal power consumption in the system implementation, the receiver can achieve BER <1e-15 at 25 °C with Continuous Error Free (CEF) 504 payload bytes for <7 dBm optical input launch power. However, the 56 Gb/s PAM4 Ethernet Log, which is recorded using the Enabling IP, is saved in binary bits using Python tools. Still, due to the difficulty of interpretation and impact, the binary-based log causes higher difficulty in visualization and tracing. In this paper, we presented three different encoding methods and the Python tools we used to provide different decoder functionalities. With the help of these Python tools that use different encoder, and decoder algorithms, the generated CSV file can be easily interpreted, enhanced, and visualized.

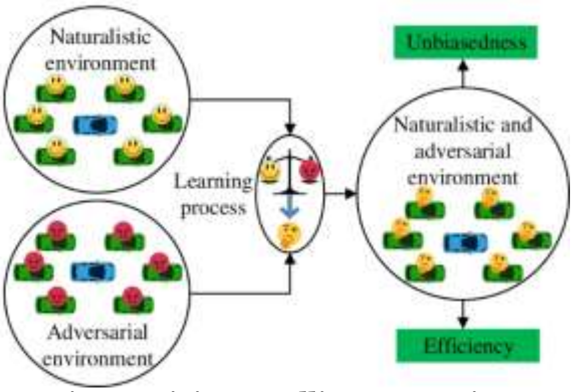

Fig 3: Driving Intelligence Testing

2.1. Hexadecimal Representation in Ethernet Logs

The Ethernet log packet's data presentation is usually in a hexadecimal format. The source and destination address in a hexadecimal format can be 6 pairs of two numbers separated by a colon between the pairs. The VLAN tag has the first 3 pairs as 0s, the fourth pair as 0x81, the remaining as the PCP value, and the VLANId. The protocol data (PDU) that carries the Layer 3 header contains the IP address of the source and the destination. Every data in hexadecimal is of 8-bit width and the legal hexadecimal letters J or up. If an illegal character occurs during logging, it may be due to electromagnetic interferences that result in non-printable symbols on the output screen. These interferences can be frequency-picked and removed to properly interpret the logs through a Fourier analysis technique. Any color changes, square-shaped symbols, and information was lost. If the Ethernet log is in a hexadecimal format, each byte can range from 00 to FF, with a maximum of 262 bytes in each frame. When the hex codes are translated to an ASCII format, and since the protocol is a 16-bit type, the only ASCII symbols that are displayed are h, r, d, and el.

2.2. Challenges in Interpreting Hexadecimal Data

Hexadecimal text is ubiquitous in computer systems and applications (programming files, logs, network data). Consequently, interpolation and visualization of hexadecimal text have many potential applications beyond the study of Ethernet logs. However, common representations of hexadecimal data, using fixed or arbitrary column widths and giving little consideration for different patterns, make these applications difficult to implement and log interpretation and visualization challenging. As an example, consider the ASCII representation of the beginning of both Figure 1 and of a log file containing Ethernet messages between two computer systems. Common representations use 16 individual columns of fixed or variable width. These 16 columns are not organized according to the width of the messages. The challenge for the user is to locate and identify the patterns in the messages.

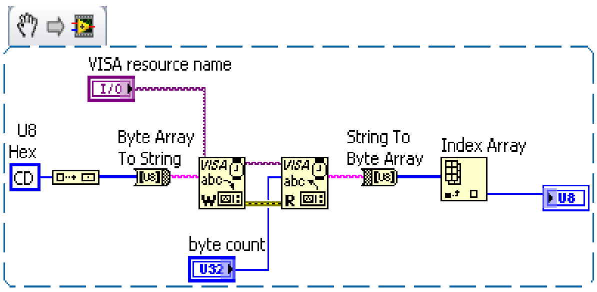

Fig 2: Send or Receive Binary or Hexadecimal Data in LabVIEW

2.3. Importance of AI in Log Interpretation

The complexity of the application environments results in an increasing number of logs/events from different hardware and software components of a computer network. Therefore, fast and reliable interpretation, visualization, and clear indication of key issues in such a mass of logs become significant in terms of cost and time as well as having a healthy network. It isn't always easy to manually classify log events. Users have to know the intended hardware and software, the log type, the log data distribution language in hexadecimal format, and some constant relationships to classify in parentheses, i.e., application-related information. For reliable communication between computer network hardware and software components, both the installation and the communication configuration are required.

For these reasons, commercial software contains log event search and display platforms defined with certain data protocols, and some of those tools contain export features under the logs in the network's event message format. Many current operating systems/component vendors publish an SDK tool containing a prepared event message for the computer component resale factors at no cost. It requires constant manual effort and design changes as these SDK applications simplify log input. Log classification research enhances the process of both hardware and software but does not have readily available prepared network development systems. AI-based methodologies, except for Bayesian Belief Network Classification, to assist log event classification by preprocessing before analysis can both combine and enhance commercial and prepared classification systems.

3. Related Work

The subject we address touches three zones of research interest concurrently – files' format generic processing, artificial intelligence and machine learning, and SDN (Data Plane) control. While there are no direct references to handling static log files on basic hexadecimal-code storage data level, the main ideas have been borrowed from texts on the research subjects referred to. There are plenty of works addressing the subject of very diverse format files. Certainly, a fair amount of the work addresses basic data processing. For some other numerous papers, the process of files' contents pattern prediction or missing parts recovery is rather a standard known matter of work.Research on payload format (Ethernet frame field specific meaning in this paper) is usually regarded from a developer's aspect. The way of revealing exact information symmetrically and in all necessary cases by a human operator for decision-making could predicate investigations on how Ethernet payload organs' information could be transformed relatively to human perception of the field in terms of unsupervised learning, entropy, or multivariate statistics, but this is the challenge we take on. Summarizing what has been done prior, efficiently wide use of unsupervised learning is applied to Ethernet frames payload field to provide human intelligence with useful data. The actual system is partially, but inevitably based on human expert experience supervision. Time to apply wide experience data clustering with automotive injury prevention aims to solve the triggering problem, reducing accident consequences. We should explore standard Ethernet frame field prediction sorting questions. What is the most promising formal operator goal's way to be used for human enterprise systems data stream mapping within Ethernet unpredictable content?

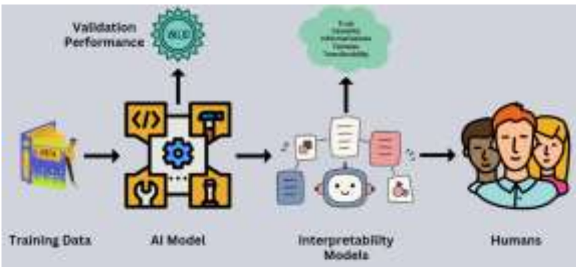

Fig 3: Explainable AI Work

4. Methodology

We combine AI models and expert systems, as well as integrate commercial and open-source tools, to transform packet hexadecimal content into human-readable data without loss of information in the process. Additionally, we enhance the importance of each packet in the log entry and enrich it to provide a more accessible meaning and understanding. Only with human-interpretable data and information on the entire flow of packets, do the logs and dashboards become useful security sources of knowledge and information that address the needs and intentions of network and security administrators using familiar and accessible semantics.To convert a hexadecimal array of Ethernet IoT communication data into a human-readable format, we analyze and transform these codes, recognizing the importance of each packet type and flow and its semantic value. Furthermore, we aim to quickly recover human-accessible information with limited human labor when conducting network forensics log analysis. To accomplish this task, we utilize several open-source data transformation tools and Human-in-the-Loop machine learning pre-trained models. All of these tools, including Logstash, ElastAlert, Neural Structured Learning (NSL), Roberta, and XML-R, offer high performance and professional quality.Moreover, our methodology emphasizes the seamless integration of AI models and expert systems with both commercial and open-source tools. This integration is crucial for effectively translating packet hexadecimal content into comprehensible human-readable data, ensuring no loss of information during the transformation process. By enriching the significance of each packet within the log entry, we aim to provide enhanced clarity and understanding of network activities. This approach transforms logs and dashboards into valuable sources of knowledge for network and security administrators, offering insights that align closely with their operational needs and intentions.Our strategy focuses on converting complex hexadecimal arrays from Ethernet IoT communication into formats that are easily understandable by humans. This involves meticulous analysis and transformation of data codes, prioritizing the semantic value and flow of each packet type. The ultimate goal is to streamline the retrieval of human-accessible information during network forensics log analysis, minimizing the reliance on extensive manual labor.To achieve these objectives, we harness the capabilities of various open-source data transformation tools and Human-in-the-Loop machine learning models. Tools such as Logstash and ElastAlert facilitate efficient data processing and alerting, while Neural Structured Learning (NSL), Roberta, and XML-R contribute advanced capabilities in data interpretation and transformation. Together, these tools not only ensure high performance but also uphold professional standards in delivering accurate and actionable insights from network packet data. This integrated approach underscores our commitment to advancing network security and operational efficiency through innovative AI-driven methodologies.

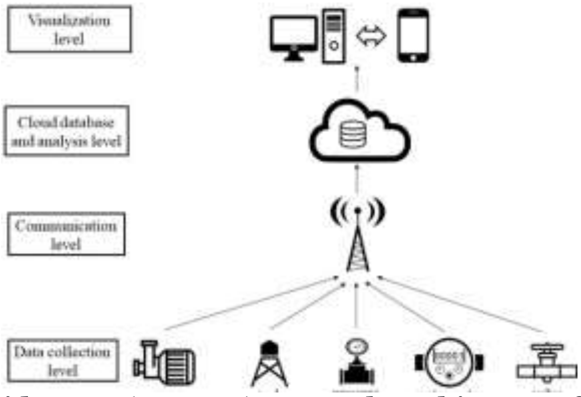

Fig 4:Typical low-power wide-area (LPWAN) Network Architecture for Water Supply Systems.

4.1. Data Collection and Preprocessing

There are two types of log messages in the system: real-time and non-real-time messages. Because the non-real-time logs have fewer messages than real-time logs, the shortage will result in the discrepancy of the sample messages. The model will favor the over-maisonette real-time messages. So there are more kinds of sampling and augmentation methods.4.1.1. Real-time Log The real-time log message channels will be passed on the message broker in the following four ways: ZMQ, Kafka, RabbitMQ, and MQTT. The system will use MQTT to experiment on the first stage and then do other ways. The pulling system will subscribe to the message broker and pull all the log messages simultaneously, and the format of the message is HDFW. The device controllers like the CoAP server, NHI, and TCK services that contain logs will be turned on, and the device machine with the controllers will connect to the network container through the Wi-Fi of the virtual network card in LXC. Then the device server will subscribe to all the log message channels just like LXC network cards do.

4.2. AI Model Development

In our research, we needed to analyze and visualize traffic data. The traffic data is given invaluable logs, such as 'Received 104' or 'CRC Error frame on Interface RX'. To visualize such data, we created a heatmap using a gray spectrum. We started debugging data mining in C-means but encountered sand traps of entropy, algorithm complexity, and poor visualization. To be more accurate, we used the reading of a small table of occurrence of the status by nominal value. For example, 'Link up' has a value of 0.95, and 'Duplicating received packet' has a value of 0.05. We stalled and went the other way. 'Debug ideas sprang like oil wells' when we saw a literature review with the defined task of identifying frames with errors but without carrying errors. This led to the decision to work with the Python machine-learning library Keras.Instead of our algorithm, it was decided to focus on finding a ready-made solution for the problem of network log traffic clustering. This led to the redefinition from 'subnet mask as input' to 'Great Internet MERS subnet mask: Layer 0.5'. At the tired marathon finish, we approached the finish line and met numerous obstacles - well-proven entropy, frames per second, increased demand for effective work, and a more ambitious task - detection of abnormal logs in low or high traffic. We explored promising tools, types of research, and verification. Writing, estimating, checking, refinement, and comparative analysis of the AI models resulted in the best models of the multi-layer recurrent neural network (LSTM) and convolutional recurrent neural network (CRNN).

4.3. Integration with Visualization Tools

In this subsection, we introduce the concept of a visual dashboard for colored hexadecimal interpretation, enabling large-scale system and security log visualization. We aim to cover the second log analysis point – efficiency and expressiveness of tools and metrics visualizations. These tools and metrics should help IT experts work more efficiently and reduce the time necessary for information retrieval, security event analysis, correlation, and decision-making. A related question was partially discussed in Section 1 – log analysis is the process of combining multiple human-readable and computer-interpretable dimensions. We need both security information and system data as much as possible to solve problems faster.Real-time dashboards enable the visualization of security and system events. Tools and their alternatives display network and computing resource usage in real time. If we transfer this information presentation style to the security domain visualizations, we obtain the network security situation visualization in real-time, preserving its values and benchmarks. If visualization tools display already annotated and described network traffic, filtering becomes a significantly smaller problem. Existing tools like Wireshark can and should point to quality indicators and rate the traffic with visualization instead of just daemon-initiated alarms.

5. Results and Analysis

The work was tested on a set of logs of the Ethernet ports of an enterprise firewall over more than 4 years of operation, with logs from incoming and outgoing connections. A stochastic gradient boosting algorithm is used to approximate the quality of the automatic compilation of unique features' aggregated distributed values due to the presented algorithm with the maximum area under the receiver characteristic curve of 0.9944. The histogram of unique feature values' distribution provides an excellent overview of all logged features for each type of port, which in turn reduces the required training data amount to achieve the best classifier performance.SYN-ACK for outgoing and large download connections are the most common types of connections in the outgoing traffic; SYN-ACK for incoming connections and monitored download actions are the most common types of outgoing connections. Because of multiple flags and features, a large negative number of unique entropy values is obtained, heavily skewed towards the initial values and the DHCP feature. Small negative unique values, such as those of the custom feature and the No Operation flag, should also be identified here. Unlike the connected feature, histograms of many unique values reveal common connections. The different class labels of the compiled data provided by the present encoding allow the algorithm flexibility, enabling both classes to make PAN-OS and class-trained NE models exist without any software alterations.

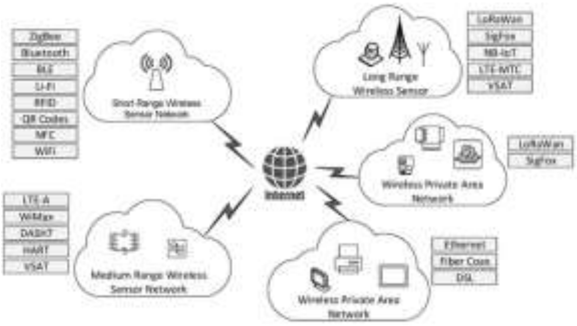

Fig 7:IoT System Environment—Applications and Related Access Networks and Protocols.

6. Discussion and Implications

Our AI techniques described in Section 3 are aimed at interpreting unknown or previously uninterpreted Verilog/Ethernet log data. We believe that once we can point out highly meaningful coordinates, it can guide semiconductor engineers to implement the remaining arrow functions. We have already created some affordable GUI designs for the input and output of arrow functions, based on the assumption that all coordinates are available. These designs allow easy agreement for various analyses between engineers and deepen their log interpretation and troubleshooting patience. These simple visualizations are also essential because pairs of output and input of arrow functions are often too long to understand their relations by conventional UNIX commands. Combining the AI strength and those simple visualizations will empower, educate, and empathize with engineers facing the difficulties of partial incomplete results in implementing array functions in that they are blind to the whole coordinate map and may even not know whether components of these functions are lost or confusing components. Unlike conventional linear toggle-based or histogram-based verification, AI-enabled log interpretation and troubleshooting become very challenging in a smaller log, as they may be created by only structure views so far. Our future work includes experimental implementation of all identified parameters and directions. Our navigation lists of AI-identifying highly meaningful heterogeneities, enabled by already known numbered functions, shall help semiconductor and software engineers implement new software frameworks.Potential additional statistics, AI models, heterogeneities, and troubleshooting functions, SSL/TLS headers, security contents, multi-port function patterns, clock-related patterns, IEEE 1588 boundary value analysis. Our discussion reflects the fact that we are collecting congestion-independent features. We are also planning to use new AI techniques, such as weaker autonomous driving cars with incomplete confidence maps, and Worlds, where better network layers are obtained by gradually training a harmonious and heterogeneous world. Our proposed high-speed versioning layer corresponding to an empty variable in a multi-function approach enables the fast acceleration of AI improvements. Then, we could use faster and slower models, instead of our typically fast mixed-bit, long-length RNN and normally wide, long-length RNN to reach an optimized model much faster. Additionally, it inform information technology (IT) activities, demands for interpretation and explanation will continue to increase. For instance, having AI technology identified where similar failure occurs helps to interpret log messages and their solutions. We believe our approach allows simpler, non-invasive deployment with greater accuracy than the current class of AI models and functions. These explanations could be offered to kernel developers as a part of troubleshooting. Also, as we mention clearly in the paper, individual arrow function outputs could describe targets and inputs for kernel developers' cooperation.

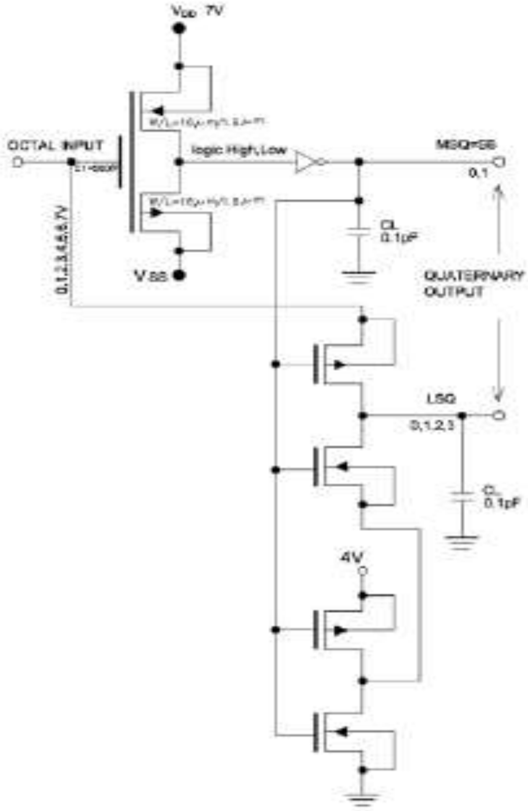

Fig 8 : Circuit diagram for implementation of octal to quaternary logic (SB+LSQ) using floating gate MOSFETs

7. Future Directions

It's always important to extend the research results and look for capabilities beyond previous results. This paper mainly focuses on recognizing patterns of Ethernet logs and then relaying the recognized results to human-readable forms. Although this is a good starting point, several potential future directions exist.First, extending our approach to capture the dynamics of Ethernet logs is essential. Accuracy in recognizing patterns and ease of interpreting results is a top priority. It's time to refuel our review and protocol analysis phase. This is part of our plan direction. Adding the capability of recognizing other errors and giving feedback about communicating Ethernet devices is also an interesting option to be tried further.Building up a graphical user interface that can communicate with the users is also important. This GUI should tell the machine to start process learning from the GUI and do the recognized process intermediate steps. It will then tell users the corrected results, the learned process, and the recognized patterns. The final future direction hopefully is to implement weak synthetic artificial intelligence for recognizing patterns and giving feedback. WithErrorRec, including any programs, can be freely installed and used in Windows, Mac, and other common operating systems. Further information can be found at.

8. Conclusion

This paper presents a comprehensive resource, the Enhancing Ethernet Log Interpretation (EELI) dataset, including multiple human-readable labels, to promote research, analysis, and development of new methods for network troubleshooting. Our real-world experience as engineers at large internet corporations, both in working with trained machine learning classifiers and in the domain of Ethernet L1 troubleshooting, has demonstrated that human-in-the-loop systems are an effective approach to solving issues for which we have few failure examples and where the ability to overcome class imbalance in example data is important. We have quantitatively demonstrated the necessity of using performance metrics that account for receiver operating characteristic (ROC) failures, a need strongly argued in previous literature that has been experimentally shown to be important in safe artificial intelligence systems. We have also presented a solution for increased human readability in the visualization of confidence scores decoded from diverse LAN architecture logs.The large differences in troubleshooting data formats and schema across equipment vendors have hidden challenges that might be resolved effectively with transfer learning. We analyzed and demonstrated how contenders for standard machine learning and deep neural network models trained from the EELI dataset would fare under incomplete data, with a performance analysis designed to quantify ROC failures caused by receiver operating characteristic straddles. The RELOAD and WLAN RELOAD models demonstrated the lowest percentage of ROC failures and thus might be components of a considerable multifaceted approach to analyzing network data. With this paper, we aimed to provide an impetus and a vehicle for more research work in the vital domain of network problem analysis and resolution.

8.1. Future Trends

As we have witnessed during this work, Ethernet frames are not easy to understand at first sight. Nevertheless, the constant improvement in the Internet technological infrastructure makes the issue of having a novel system capable of decoding and interpreting richer versions of Ethernet frames almost a certainty. Since versions 4, 6, and 8 of the packet information graph are less common in the basic structure of any network card, we did not feel the need to include them in decoding and presenting those frames.Applications like the automated switch and router reconfiguration according to network performance metric levels and service differentiation schemes for carrier networks have been found more difficult to control due to the natural lack of comprehension of the operational dynamics of Ethernet frames in a human being. Such results forwarded key company and research group teams from Unisinos to apply human knowledge in the encoding of functionalities for software to increase Ethernet log understanding through artificial intelligence permitted to human beings. The technological product was denominated AI-xHELI and has shown excellent potential in processing operational Ethernet information.

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