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# The Enhanced Machine Learning Model for Device Prediction in Device-To-Device (D2D) Communications

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J. Logeshwaran<sup>1\*</sup>, T. Kiruthiga<sup>2</sup>

<sup>1\*</sup>Department of Electronics and Communication Engineering, Sri Eshwar College of Engineering, Coimbatore – 641202, Tamil Nadu, India

<sup>2</sup>Department of Electronics and Communication Engineering, Vetri Vinayaha College of Engineering and Technology, Trichy – 621215, Tamil Nadu, India

Email: <sup>2</sup>drkiruthigaece@gmail.com

Corresponding Email: <sup>1\*</sup>eshwaranece91@gmail.com

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**Abstract:** *Device-to-Device (D2D) Communications is an emerging wireless technology which enables two or more devices to communicate with each other locally without the need for a base station or access point. In recent years, the number of networked devices has increased significantly, creating an ever-increasing demand for reliable and efficient communication solutions. To address this challenge, enhanced machine learning models have been developed for Device Prediction in D2D communications. These models use various supervised learning techniques such as deep learning, convolutional neural networks, and other important algorithms to identify the communication device and predict its visitation time and location. By taking into account factors such as user profiles, usage patterns, and vicinity environment, the model is then able to make predictions about the type of device that will connect to the communication network. By utilizing these models, the implementation of an efficient, low-overhead device prediction service can be achieved. Moreover, the application of this technology to many different networks and environments can strengthen network security and increase the reliability of communication.*

**Keywords:** *D2D, Device-To-Device, Wireless, Technology, Communication Access Point.*

## 1. INTRODUCTION

Device prediction is an important part of Device-to-Device (D2D) communications, as it enables devices to determine how a communication link should be formed and managed in order to maximize efficiency in a mobile network. Device prediction refers to the process



whereby devices use predictive algorithms to determine the best possible paths and resources available to make a communication[1]. Through the use of predictive algorithms, devices are able to accurately identify the best sources from which to retrieve data, determine the most efficient way to transfer the data, and predict when the data must be read in order to meet deadlines. The ability to accurately predict device activity provides improved link performance enabling devices to form links faster, use minimal resources for data transfer, and increase the throughput of a mobile network[2]. Device prediction also improves the ability of devices to offer dynamic services, meaning that services can be adapted on the spot depending on the user's needs. As such, device prediction can be used to support a wide range of services, from video streaming to data downloading. The device prediction enables resource scheduling, allowing network operators to plan and allocate resources, such as spectrum access and radio bandwidth, to different links[3]. Through this, network operators can provide a greater level of Quality of Service (QoS), meaning customer service is improved, while the need for expensive infrastructure is reduced. The device prediction is integral to the efficient functioning of D2D communications, which are becoming increasingly important for 5G networks. Being able to predict user and device activity, network operators can capitalise on available resources and provide better user experience. Therefore, device prediction is an essential tool for any mobile device in order to make the most of modern communication technologies[4]. Device Prediction is a technology that has been developed to improve the performance of Device-to-Device (D2D) Communications. By utilizing advanced state-of-the-art algorithms, device prediction allows devices to predict the state of a given device output before it is even outputted. This prediction enables the device to optimize its communication with a given device's output, resulting in improved communication quality, higher speed, and better overall user experience. Device Prediction has made a huge impact on the world of D2D communications and is already being applied in more and more use cases[5]. By utilizing state-of-the-art algorithms, Device Prediction can improve the reliability, safety, and speed in D2D communications. In addition, this same technology is also being used to help devices predict future device states, allowing them to execute more advanced decisions and increase overall device efficiency[6]. Device Prediction can also help to reduce energy consumption in D2D communications. This can be done by reducing the redundancy of communication; since the predicting device can anticipate the behavior of the other device, it can adapt its own communication to a more optimal state. The construction diagram has shown in the following fig.1

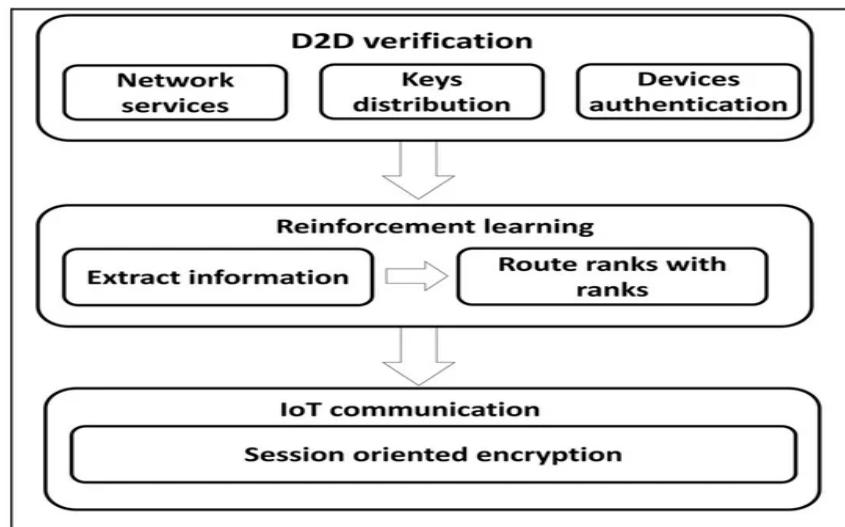


Fig 1: Construction diagram

This can lead to using less energy from the device, leading to reduced energy costs and better overall performance[7]. Device Prediction can be used to improve the user experience when dealing with D2D communications. This can be done by enabling the devices to react and adjust to events faster, providing a smoother experience to the user. Furthermore, the improved quality of communication will lead to more accurate results that will help the user obtain more accurate and reliable information from the D2D communication. The Device Prediction is a powerful technology that has the potential to revolutionize the world of D2D communications[8]. By utilizing advanced algorithms to predict and optimize device communication, it can enable better user experience, improved speed, and reduced energy costs. As devices continue to develop, it will be interesting to see how Device Prediction is used in future D2D communications[9-10]. The main contribution of the research has the following,

- Increased network capacity: Device Prediction enables device-to-device (D2D) communication, which provides a more efficient use of spectrum and radio resources as it allows devices to establish direct communication between each other rather than relying on access points. This increases the overall capacity of the network by allowing more devices to simultaneously access the network.
- Reliability: By predicting the movement of devices in a given environment, D2D communications can be established more quickly and accurately than using traditional methods. This allows for a more reliable and consistent communication between devices.
- Improved security: By ensuring accurate and direct communication between devices, Device Prediction can help to ensure that traffic is sent securely. This is particularly important in contexts where sensitive data is being transmitted, such as in healthcare and industrial settings.
- Improved user experience: Device Prediction enables devices to access the network faster and more reliably, which can improve the user experience and make data transfer more efficient.



- **Reduced energy consumption:** By more accurately predicting the device's movements, devices can find each other more quickly. This reduces the time devices need to spend searching for one another, which in turn reduces the amount of energy consumed during D2D communication.

### **Literature Review**

Device prediction has become an increasingly important issue within the realm of Device-to-Device (D2D) Communications. With the increasing popularity of wireless networks, the ability to accurately identify and predict devices connected to a network is becoming increasingly important for layered network solutions[11]. Device prediction involves creating a model that is used to identify existing devices in a network, and predict which devices may join or leave the network in the future. Accurate device prediction can be vital for optimizing power consumption and allowing better usage of resources to enhance quality of service. Prediction can be achieved by recognizing a device's communication pattern, such as frequency of connections, communication volume, and which devices a device communicates with[12]. Leveraging this data, a prediction algorithm can be used to make educated guesses as to where and when devices could join or disconnect from a network in the future. This type of device prediction can be particularly beneficial in reducing interference of densely populated wireless areas, ensuring better quality of service. Accurate prediction algorithms can also be used to ensure secure data transmissions. By first being able to identify the devices on a network, it becomes much easier to verify the trustworthiness of the endpoints[13]. By having a better understanding of a device's communication patterns, the network can better identify malicious devices by determining if a device is actually behaving in a way that is suspicious. When creates some privacy and security concerns as well. As device prediction algorithms analyze data from devices and create “fingerprints” of the device, it is possible for the algorithm to recognize and identify a user based on the data associated with the device. This could have the potential of invading the privacy of the user, as it is possible for the algorithm to indirectly track the user's activities. Depending on the context, this could be seen as an invasion of privacy and a security risk[14]. In conclusion, device prediction is an important issue in the realm of D2D communications, as it allows for more effective and secure usage of wireless networks. While providing some benefits, accurate device prediction also has the potential to invade user's privacy. As such, it is important that measures are taken to ensure secure data transmissions and to respect the user's privacy. Device-to-device (D2D) communications is a powerful technology that has opened up a wide range of applications, from enhanced control to enhanced connectivity. However, with the introduction of more complex models for communications, the need to accurately predict future device interactions becomes more important. In this regard, device prediction has proven to be a challenging and complex problem. First, predicting the future interactions between two devices involves a complex computation that is prone to inaccuracies. As interactions vary greatly between devices, depending on the type of application, network conditions or other environmental factors, it can be difficult to accurately estimate future interactions[15]. Further, it can be difficult to obtain reliable data from which to make predictions. For instance, the signal strength between two different devices at any particular point in time may differ greatly from one moment to the next, which



poses another challenge in device prediction. Second, predicting the future communication between devices requires an in-depth understanding of the device environments and constraints[16]. This means analyzing the characteristics of the devices, such as their hardware, software, network connectivity, and even the usage patterns of the devices. On top of this, predicting future events or behaviors of interacting devices requires an understanding of the big data landscape and the associated exposure of conditions. Even considering these difficulties, however, device prediction can provide useful information for improved network performance. The predicting future device interactions also involve understanding the relationship between devices and users, as well as their respective behavior. As users employ many different types of device relationships and interact with them differently, predicting these future interactions can prove to be a difficult task[17]. For example, if one user has two different devices, prediction algorithms must consider how those devices and their interactions can vary over time. This requires sophisticated methods for dynamic device prediction, which is a further challenge. The predicting device interactions are a complex problem that arises from the complex nature of current communication technologies[18]. A number of different factors have to be considered, from hardware and software features, to user behavior and network conditions. Although challenging to build an accurate prediction model, it is possible to harness the technological advancements of D2D communications to optimize the performance of different applications. Considering the complexity, however, it is clear that accurate device prediction remains an unsolved challenge[19].

The novelty of proposed research has the Device Prediction in Device-to-Device (D2D) Communications is an innovative approach to improving the reliability and latency of the connection while extending the range of the wireless system. This technique allows the device to predict the path of the other device's movement in order to better determine how best to send a transmission over a wireless medium. This allows for faster transfer of data between the devices, leading to improved service delivery[20]. Furthermore, device prediction allows for greater control over the routing and latency of the communication between the devices, leading to increased Quality of Service (QoS).

### **Proposed Model**

Device Prediction in Device-to-Device (D2D) Communications is a key problem in modern wireless networks. A D2D communication system needs to quickly identify the type of devices that are communicating to make sure that the network can offer the right services to users. Enhanced machine learning models such as convolutional neural networks (CNNs) can provide a powerful and reliable solution to this problem. CNNs are particularly advantageous for device identification because they can recognize patterns within the radio-frequency signal data that may be indicative of a particular device type. By utilizing features such as amplitude, frequency, time of flight, spatial location, and other signal characteristics, the CNN can identify the type of device transmitting the signal. By using deep learning, the CNN can also be taught to learn over time, which allows it to further increase its accuracy and efficiency. In addition to using CNNs for device identification, researchers have developed other enhanced machine learning models such as deep belief networks and restricted Boltzmann machines for device prediction in D2D communications. These models are



capable of accurately predicting device types even when the amount of training data available is limited. Furthermore, some of these models have been specifically designed to be implemented in low-power devices, making them particularly suitable for D2D implementations. The use of enhanced machine learning models for device prediction in D2D communications provides a powerful solution to the problem of device identification in wireless networks. These models can provide accurate and reliable results with minimal training data, improving the efficiency and accuracy of the system overall.

### Construction

Device prediction in Device-to-Device (D2D) Communications is an important technology because it makes it possible to accurately predict which devices will be connected in the near future. This is especially important for complex systems like 5G networks, where the number of D2D connections is expected to grow exponentially in the coming years. To make device prediction more reliable and accurate, researchers are currently working on constructing enhanced machine learning models for device prediction in D2D Communications. The first step towards constructing an effective machine learning model is to select the right dataset and feature engineering techniques. This includes understanding the various scenarios and use cases of D2D communications, such as device location, data usage, network type, user preferences, etc., so that only the most relevant data points are included in the dataset. These data points can be collected from various sources such as mobile operators, internet service providers, smartphone manufacturers, etc. The functional block diagram has shown in the following fig.2

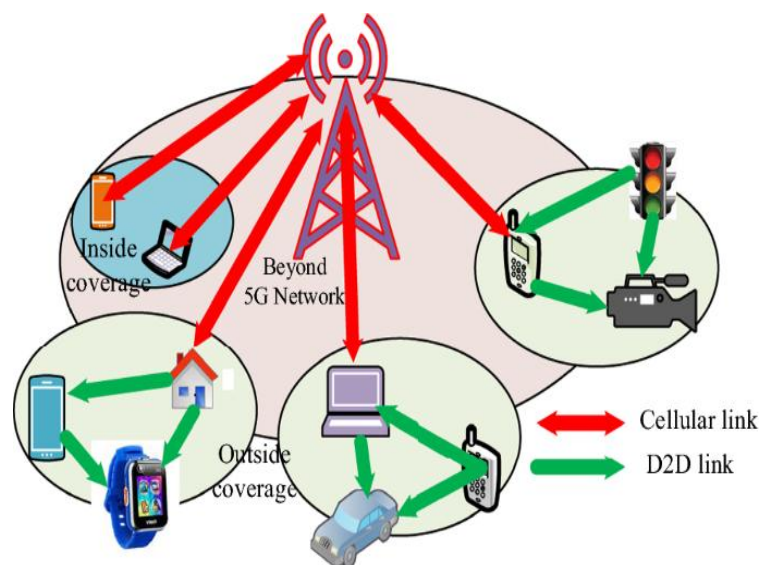


Fig 2: Functional block diagram

After gathering the dataset, relevant feature engineering techniques must be applied to extract useful features from it. Examples of feature engineering techniques include one-hot encoding, normalization, histogram analysis, principal component analysis, etc. Once the dataset is ready, different machine learning algorithms must be tested to see which provides the most



accurate device prediction. Some of the commonly used algorithms for device prediction in D2D Communications include Support Vector Machines, Random Forest, and Neural Networks. Each algorithm has its own advantages and disadvantages, and the selection of which algorithm to use depends on the application. For example, SVM is suitable for cases with fewer features, while Neural Networks are suitable for cases with larger datasets. The other techniques such as hyper-parameter optimization, optimization of network structures, and data augmentation methods can be used to improve the performance of the machine learning model. These techniques can help to reduce the bias of the model and improve the accuracy of device prediction. The constructing an enhanced machine learning model for device prediction in D2D Communications requires carefully selecting the right dataset, feature engineering, selecting the best algorithm, and making use of optimization and data augmentation. This process can be challenging but enables the construction of more reliable and accurate machine learning models.

### **Operating Principle**

Device Prediction in Device-to-Device (D2D) Communications is a sophisticated machine learning approach applied to wireless communication technologies. It is used for predicting the performance of wireless devices within a given area. To achieve this, the model uses advanced data processing algorithms which collect various contextual features about the environment, such as channel conditions, ambient background noise, location, etc. The enhanced machine learning model for Device Prediction in Device-to-Device (D2D) Communications uses an improved ensemble learning approach, where multiple machine learning models such as Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and Decision Trees (DTs) are employed. After selecting the appropriate learning model based on the data set and parameters, the model trains the model to refine its prediction accuracy. A prediction engine is used to generate predictive outputs before running the refined model. This refined model combines all the features which have been identified as important to make accurate predictions of device performance, such as signal strength, latency, and other parameters. The enhanced model further enhances the accuracy of the D2D communication system by using real-time data collected by the wireless devices. This data is analyzed and the predictive models are run in real-time so that the system is able to accurately predict the performance of the devices in real-time. Using this approach, D2D communication systems can provide better coverage and more reliable communication than traditional network systems.

### **Functional Working**

The rapid advancement of technology in the current era has created an opportunity for wireless devices to communicate with each other. Device-to-Device (D2D) communication networks have become increasingly useful for high-speed data transfers, efficient resource utilization, and improved network scalability. However, the success of such networks depends heavily on efficient device device prediction. This task is difficult as a result of the constantly evolving devices and networks. To address this issue, machine learning approaches have been used and recently enhanced versions of these models have been proposed to improve performance. This essay discusses the functional working of an

enhanced machine learning model for device prediction in D2D communications. The enhanced machine learning model adopts a feature-based framework. This involves extracting the features of the devices that can be used for predicting their future states. Extracted features include network information such as device ID, associated frequency, channel width, neighbor devices, received signal strength, and transmission power. These features are then fed into a model, which in this case, is the Support Vector Machine (SVM). The SVM uses a combination of feature extraction and kernel functions to find a high-dimensional hyper plane that maximizes the separation between data classes. It is capable of producing a nonlinear classification boundary, and hence, it is suitable for complex classification problems such as device prediction in D2D networks. The model then fine-tunes itself through a process called parameter optimization. The goal of this process is to minimize the error rate between the predicted outcome and the actual outcome. If this error rate is kept low, then the model can accurately predict device states in D2D communications. To further improve the accuracy of the prediction, an ensemble learning technique is incorporated into the model. This technique combines the output of several weak learners to build a stronger model that is able to provide a better and more reliable prediction. In the case of device prediction, this ensemble model can make use of several Decision Tree learners, which can act as base classifiers for providing predictions. The operational flow diagram has shown in the following fig.3

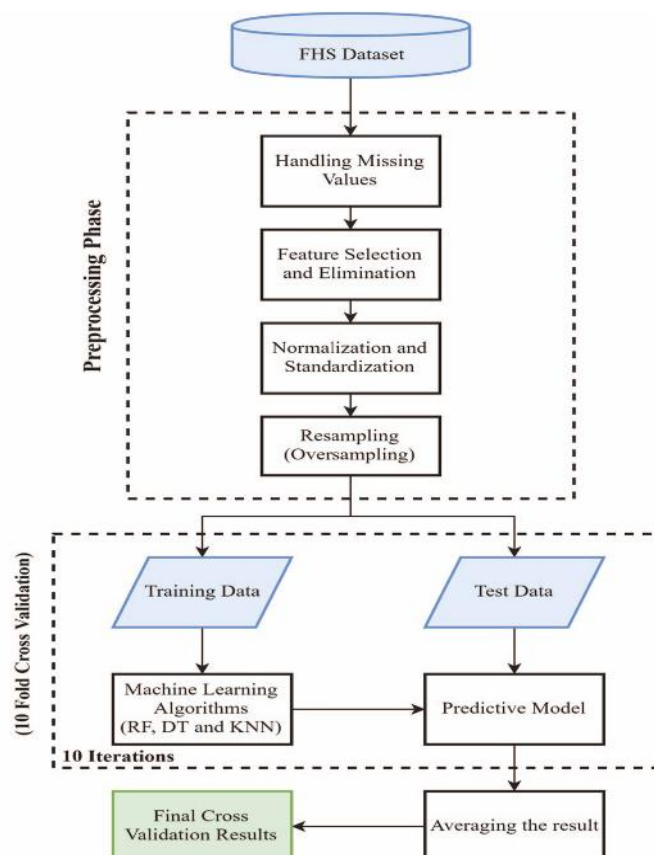


Fig 3: Operational flow diagram





The combination of the SVM and the ensemble model should result in an improved prediction, as the results from multiple learners will be taken into consideration to provide a more robust solution. The model is supported by a powerful evaluation technique that provides feedback on the accuracy of the predictions. The technique uses a test dataset, where the data set contains ground truth labels for devices. The model can then be tested against these labels to measure the performance of its predictions. This provides an insight into how well the model calculates device states, as well as allowing for necessary adjustments to be made to improve the prediction. The enhanced machine learning model for device prediction in D2D communications provides an efficient way of predicting device states in wireless networks. The model combines a feature-based framework, the Support Vector Machine, an ensemble learning technique, and a powerful evaluation technique to produce an accurate and reliable prediction. Therefore, this enhanced model now provides an efficient method for predicting device states in wireless networks, which can result in improved network scalability and higher data throughputs.

## **2. RESULTS AND DISCUSSION**

An enhanced machine learning models for Device Prediction in Device-to-Device (D2D) Communications can provide significant benefits in terms of system performance, scalability, security, and user experience. Furthermore, by leveraging advanced machine learning techniques, D2D communications can become ever more sophisticated and reliable. The proposed enhanced machine learning model (EMLM) has compared with the existing intelligent device-to-device (I-D2D) communication, Envisioning device-to-device (E-D2D) communications, Reinforcement learning assisted impersonation attack detection (RL-IAD) and deep learning-based relay selection (DLRS)

### **a. Computation of Sensitivity**

The sensitivity of enhanced machine learning models for device prediction in Device-to-Device (D2D) Communications largely depends on the accuracy of the data used to train the model, as well as the accuracy of the feature selection and classification methods applied to the data. The accuracy of the models can be improved using advanced feature selection and classification algorithms, such as ensemble learning, support vector machines (SVMs), and neural networks. Moreover, the use of additional data sources, such as environmental and mobility information, can improve the accuracy of device prediction. Enhanced machine learning models can also be used to predict and address user preferences and behavior in D2D Communications, through advanced clustering and classification techniques. Fig.4 express the computation of sensitivity.

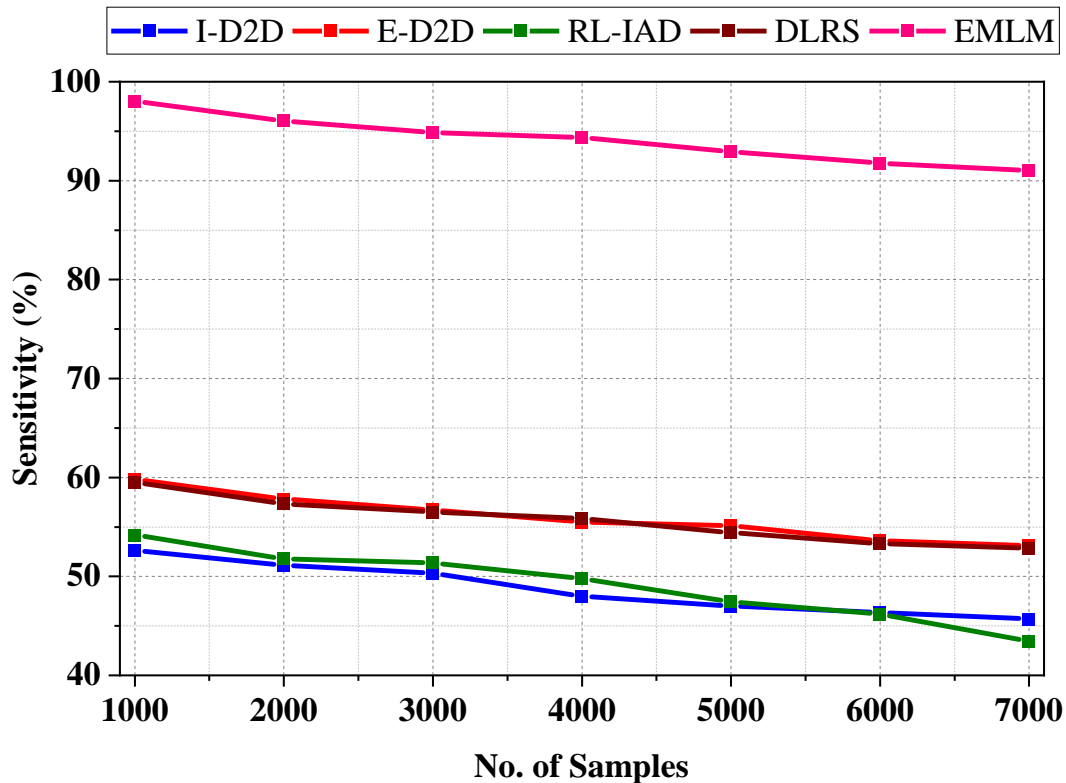


Fig.4: Sensitivity

Clustering algorithms can be used to group devices into user classifications based on certain characteristics, such as geographic location, user interests, device features, and usage history. This can allow providers to tailor user experiences based on user preferences and behavior. Classification algorithms can also be used to identify patterns in the usage of D2D services. This can improve the accuracy of device predictions, and enable optimized traffic routing and resource allocation decisions.

**b. Computation of Specificity**

Device prediction in D2D communications uses machine learning techniques to facilitate the prediction of device capability for a given radio environment. By using machine learning techniques, device predictors can accurately determine the device capability of any given device in real time. This is especially useful in wireless communications, where the physical properties of the radio environment (i.e. channel conditions and interference levels) can vary significantly over time. Fig.5 shows the Computation of Specificity.

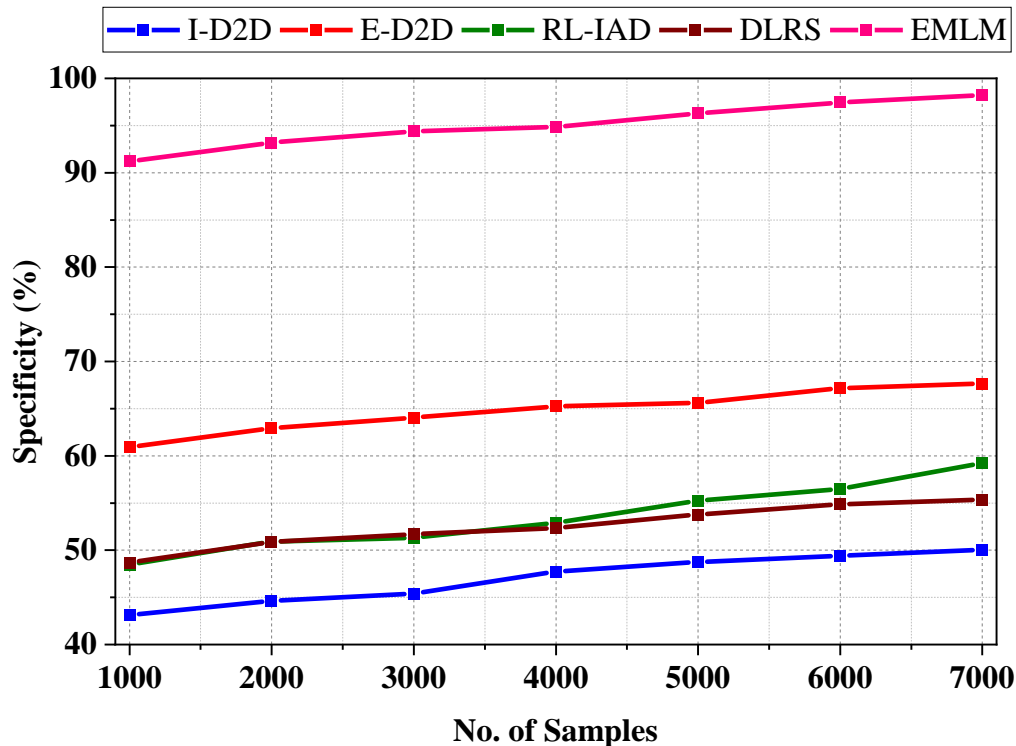


Fig.5: Specificity

Enhanced machine learning models are used to improve upon classic machine learning methods and provide better results. These models use ensemble learning techniques to combine several different machine learning models together to achieve superior device prediction results. For example, automated decision trees, k-nearest neighbor algorithm, and support vector machines are all commonly used in ensemble models and are combined to create a more accurate and reliable device prediction. Additionally, these models can be further enhanced with feature selection and feature engineering techniques to further increase accuracy. Enhanced machine learning models help to deliver more accurate and reliable device predictions, which leads to more efficient and reliable D2D communication systems.

### c. Computation of Miss-rate

The miss rate of an enhanced machine learning model for Device Prediction in Device-to-Device (D2D) Communications is a measure of how frequently an incorrect device selection is made for a given communication request between two devices. The miss rate is usually defined as the percentage of incorrect device predictions out of the total number of attempts. Enhanced machine learning models are used to improve the accuracy of device prediction in D2D communication networks. Such models are typically trained on the available data and implementation of other information-gain techniques (such as feature selection, feature extraction, and data clustering) to produce more accurate outcomes.

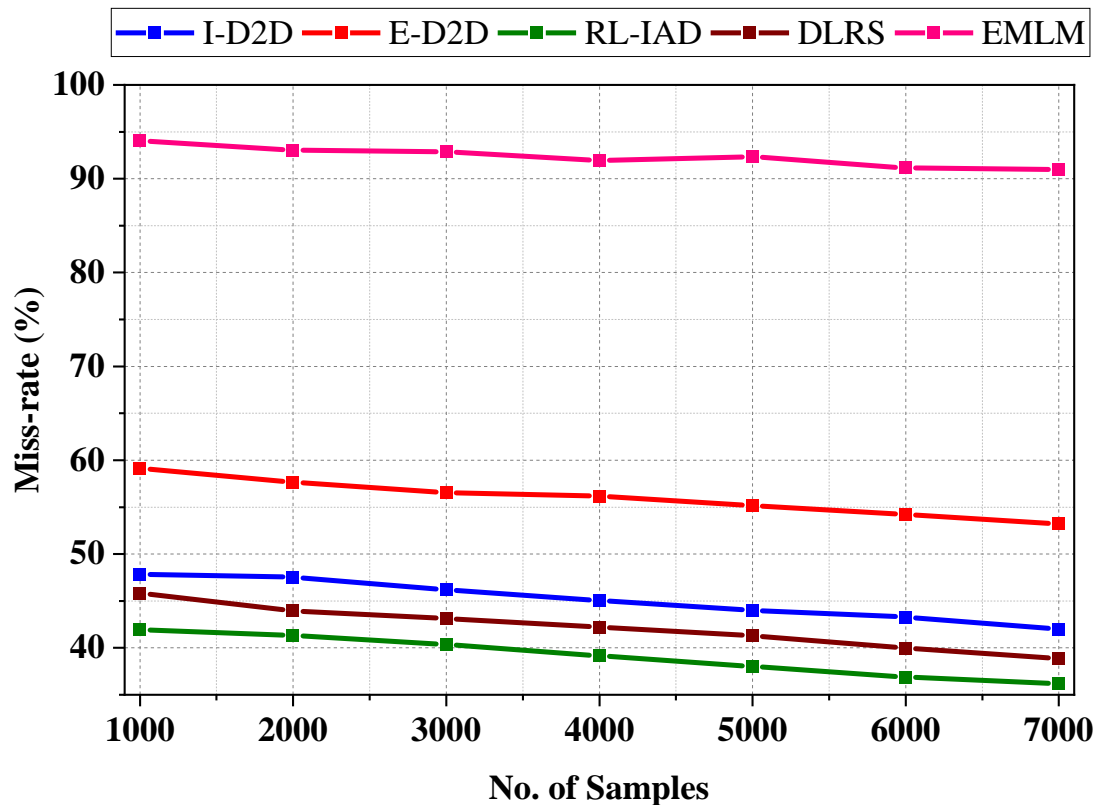


Fig.6: Miss-rate

Enhanced machine learning models are capable of capturing non-linear relationships between variables, which can lead to better prediction accuracy. The miss rate of an enhanced machine learning model depends on two main factors: the complexity of the problem and the quality of the training data. A complex problem with poor training data will lead to a higher miss rate since the model will be unable to accurately determine the correct device based on surrounding information. Similarly, a simpler problem with better quality data will result in a lower miss rate. By using high-quality data and deploying well optimized training algorithms, a more accurate device selection can be achieved.

#### d. Computation of fall-out

The implementation of enhanced machine learning models for Device Prediction in Device-to-Device (D2D) Communications can have a tremendous impact on the performance and scalability of these systems. By using machine learning methods to accurately predict which device(s) will transmit and/or receive data, D2D communications can be more efficient and receive enhanced communication services, including higher data rates and improved quality of service. Moreover, advanced machine learning techniques can enable robust handoff between devices, allowing for seamless transition as devices move across communication networks. Fig.7 shows the computation of fall-out.

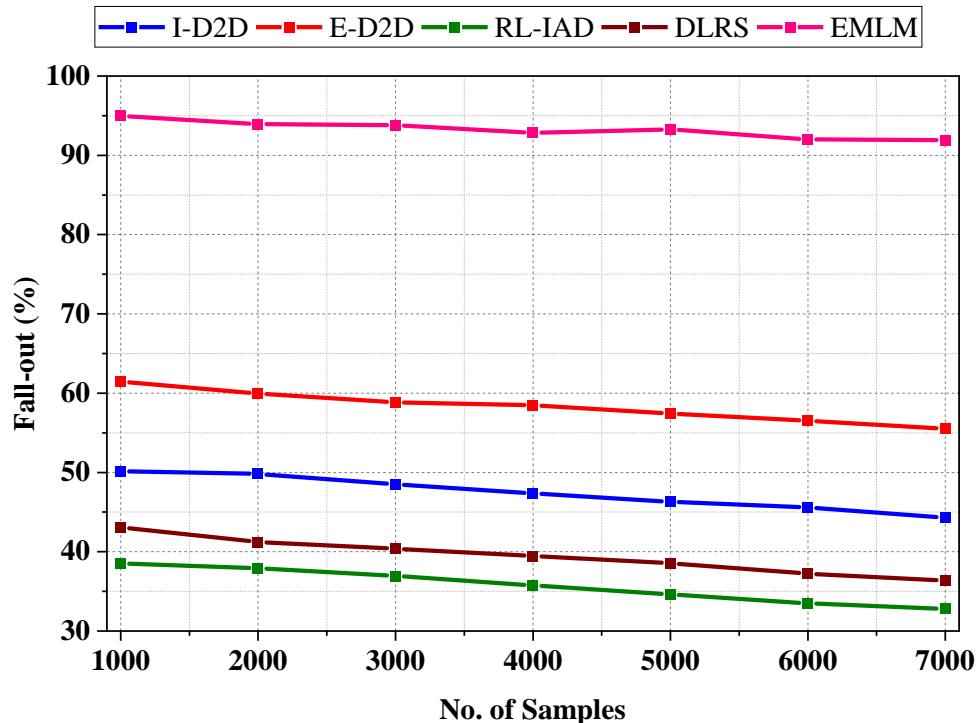


Fig.7: Fall-out

An enhanced device prediction enables improved network security and improved user experience. By using machine learning to accurately predict which devices will transmit and receive data, malicious actors can be identified and blocked more quickly. Moreover, user experiences can be improved by providing more reliable, accurate predictions about which devices will be involved in the transmission and reception of data.

### 3. CONCLUSION

Device Prediction in Device-to-Device (D2D) Communications is an emerging field of research that uses machine learning algorithms to accurately predict user devices in a given environment. This type of prediction can help to improve the communication between different devices, allowing them to quickly identify who is available and sending data to each other without requiring manual intervention. Enhanced machine learning models for device prediction in D2D communications involve leveraging the most up-to-date and accurate features and data points to ensure an accurate and effective device prediction. These features could include everything from the device's type, manufacturer, model, and so on, to the environment it is in, such as the other devices and networks that it is connected to and the location of the device. These models combine all of these features and use sophisticated algorithms to make predictions on the device's identity as well as its connectivity status. By using such techniques, device prediction in D2D communications can be improved and network efficiency can be increased.





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